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PREFACE

Editor of Techno Nusa Mandiri : Journal of Computing and Information Technology, said praise and gratitude to the presence of Allah S.W.T, creator of the universe who mastered knowledge as wide as heaven and earth, for the abundance of grace and gifts that have been given to TECHNO editors to publish TECHNO Vol. 20, No. 2 September 2023, which is used by lecturers, researching, and professionals as a medium or media to publish publications on the findings of research conducted in each semester.

TECHNO is published 1 (one) year for 2 (two) times at the end of each semester, TECHNO editors receive scientific articles from the results of research, reports / case studies, information technology studies, and information systems, which are oriented to the latest in science and information technology in order to be a source of scientific information that is able to contribute to the increasingly complex development of information technology.

The editor invited fellow researchers, scientists from various tertiary institutions to make scientific contributions, both in the form of research results and scientific studies in the fields of management, education, and information technology. The editors really expect input from readers, information technology professionals, or those related to publishing, for the sake of increasing the quality of journals as we all hope.

The editor hopes that the scientific articles contained in the TECHNO scientific journal will be useful for academics and professionals working in the world of management, education, and information technology

Chief Editor

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DIAGNOSE OF MENTAL ILLNESS USING FORWARD CHAINING AND CERTAINTY FACTOR

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Abstract— *The prevalence of mental disorders in Indonesia is increasingly significant, as seen from the 2018 Riskesdas data. Riskesdas records mental, emotional health problems (depression and anxiety) as much as 9.8%. This shows an increase when compared to the 2013 Riskesdas data of 6%. Based on these data, it can be said that many people still suffer from mental disorders. Meanwhile, the number of medical personnel, medicines and public treatment facilities for people with mental disorders is still limited. In addition, the lack of public awareness, concern and knowledge about mental health causes a lack of public interest in consulting a psychologist, so people tend to self-diagnose. One solution for self-diagnosis is to use an expert system. This study developed an expert system using the forward chaining method and certainty factor. Based on the research conducted, the results are as follows. First, the expert-based system that has been developed can help provide the results of a diagnosis that is carried out before there are complaints and will be detected early by efforts to increase awareness of the prevention of mental illness and reduce the tendency to self-diagnose. Second, applying the forward chaining method and certainty factor to this expert system can produce an accuracy rate of 95.918%. An expert has also validated these results; in this study, the expert was a psychologist at a hospital in Yogyakarta.*

Keywords: *Certainty Factor, Diagnosis, Expert System, Forward Chaining, Mental Illness.*

Intisari—Prevalensi jumlah gangguan jiwa di Indonesia semakin signifikan dilihat dari data Riskesdas tahun 2018. Riskesdas mendata masalah gangguan Kesehatan mental emosional (depresi dan kecemasan) sebanyak 9,8%. Hal ini terlihat peningkatan jika dibandingkan data Riskesdas tahun 2013 sebanyak 6%. Berdasarkan data

tersebut dapat dikatakan bahwa masih banyak masyarakat yang menderita gangguan jiwa. Sementara jumlah tenaga medis, obat-obatan dan tempat pengobatan umum bagi penderita gangguan jiwa masih terbatas. Selain itu, kurangnya kesadaran, kepedulian dan pengetahuan masyarakat mengenai Kesehatan mental menyebabkan kurangnya minat masyarakat untuk berkonsultasi dengan psikolog sehingga masyarakat cenderung untuk melakukan self-diagnosis. Salah satu solusi untuk self diagnosis ialah dengan menggunakan sistem pakar. Pada penelitian ini sistem pakar yang dikembangkan menggunakan metode forward chaining dan certainty factor. Berdasarkan penelitian yang dilakukan hasilnya sebagai berikut. Pertama sistem Pakar berbasis yang telah dikembangkan dapat membantu memberikan hasil diagnosis yang dilakukan sebelum adanya keluhan dan akan di deteksi dini dengan Upaya meningkatkan kesadaran pencegahan terhadap gangguan jenis mental illness dan mengurangi kecenderungan untuk melakukan self diagnosis. Kedua dengan menerapkan metode forward chaining dan certainty factor pada sistem pakar ini dapat menghasilkan tingkat akurasi sebesar 95,918%. Hasil ini juga telah divalidasi oleh seorang pakar dimana pada penelitian ini pakarnya seorang ahli psikologi pada salah satu Rumah Sakit di Yogyakarta.

Kata Kunci: *Certainty Factor, Diagnosa, Sistem Pakar, Forward Chaining, Mental Illness.*

INTRODUCTION

Mental health disorders are conditions in which an individual has difficulty adjusting to the needs around him. The inability to solve a problem causing excessive stress makes the individual's

mental health more vulnerable, and eventually is declared to have a mental health disorder (RI, 2020b).

The prevalence of mental disorders in Indonesia is increasingly significant, as seen from the 2018 Riskesdas data. Riskesdas records mental, emotional health problems (depression and anxiety) as much as 9.8%. This condition showed an increase compared to the 2013 Riskesdas data of 6%. The high increase in emotional and mental health problems based on age group, the highest percentage was at the age of 65-75 years and over, as much as 28.6%, followed by the age group 55-64 years, as much as 11%, then the age group 45-54 years and 15-24 years had a higher percentage—the same as 10%. Furthermore, of around 14.5 million people with depression and anxiety, only about 9% are undergoing medical treatment (RI, 2020a).

Furthermore, the prevalence of severe mental disorders, such as schizophrenia, reaches around 400,000 people or as much as 1.7 per 1,000 population. Based on these data, it can be said that many people still suffer from mental disorders. Meanwhile, the number of medical personnel, medicines, and public treatment facilities for people with mental disorders is still limited (Mariyati et al., 2021; Yulianti & Astari, 2020).

The amount of information that is easy to find on the internet and other articles for self-diagnosis is one of the factors behind the increase in mental health disorders. The lack of public awareness, concern, and knowledge about mental health causes a lack of public interest in consulting a psychologist, so people tend to self-diagnose. According to (Borghouts et al., 2021) self-diagnosis or self-diagnosis is an effort to decide that one has a disease or disorder based on available information about knowledge related to perceived experience. With the ease of access to information via the internet and articles when self-diagnosis, it is concluded that self-diagnosis is not recommended because it is detrimental to oneself and can worsen the condition if one does not get appropriate treatment (Marbun & Santoso, 2021; Maskanah, 2022).

Based on the existing problems, a system is needed that can provide information on the results of examinations that were carried out before there were complaints and will be detected early in an effort to increase awareness of the prevention of mental disorders by building an expert system. An expert system is a computer system that is capable of imitating the reasoning of an expert with expertise in computer knowledge which, in principle, works to provide a definite solution like that of an expert (Alshawwa et al., 2019; Hayat et al., 2019). In order to get an accurate diagnosis of a type of mental illness, testing is needed with various methods so that you can find out which method is

better. Until now, there is no guarantee that a diagnostic method used is the best method (Alsagheer et al., 2021).

Several studies on expert systems in the health sector have been carried out. Research conducted by Widodo et al. (Widodo & Jaya, 2018) used an expert system to diagnose the level of depression in final-year students using the certainty factor method. The result of this research is to implement the certainty factor method, which can diagnose the level of depression in students, and it can be concluded that the results of the comparison and accuracy are 97%, with these results helping psychologists/experts in diagnosing the level of depression in students. Similar research was also conducted by Sukiakhy et al. (Sukiakhy et al., 2022), who used the certainty factor method to diagnose mental disorders in children and adolescents. With the existence of an expert system, it is hoped that it can provide knowledge and can assist parents in carrying out early self-diagnosis of mental disorders that their children experience independently.

On the other hand, Aldisa (Aldisa, 2022) also conducts research on implementing expert systems for diagnosing mental health conditions. This study used the forward chaining method for the diagnostic process. The results of this study indicate that the resulting system is faster and easier to provide an understanding of the types of mental health conditions; the state of the diagnosis results and the alpha test obtained 51%, so it can be concluded that the system is feasible to use. In addition, Sholeha et al. (Sholeha et al., 2023) conducted a similar study using the forward chaining method. The result is that the resulting expert system can determine the level of depression based on the symptoms the user selects. The level of depression the system generates is normal, mild, moderate and severe. Then the system's accuracy level reaches 86.67% from 15 data owned by experts 13 data is the same as the system.

Based on various studies that have been carried out, in this study an expert system will be proposed using the Forward Chaining method to conduct symptom tracing and apply the Certainty Factor method to diagnose mental illness certainty results. This combination is done to obtain better results in diagnosing. There are two contributions to this research. First, the system built can be used to help make an early diagnosis of mental illness with accurate results. Both of these studies can be a reference in developing expert systems, especially for diagnosing mental illness.

MATERIALS AND METHODS

This section will discuss materials and methods together with the flow of this research,

which is divided into four main stages: Data Acquisition, Knowledge Representation, System Development and System Testing. Following figure 1 is the research workflow.

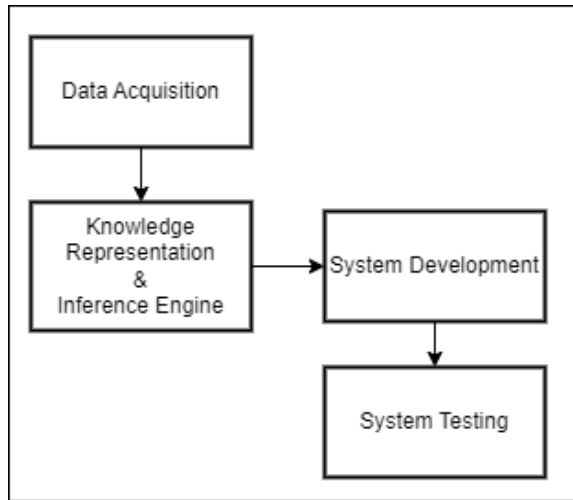


Figure 1. Research Workflow

The following points A to D are an explanation of each stage in this research.

A. Data Acquisition

Data acquisition is the stage of data collection to develop this expert system in the form of data on types of mental disorders and supporting symptom data obtained from interviews with a psychologist or psychologist at a hospital in Yogyakarta.

B. Knowledge Representation and Inference Engine

Knowledge representation is a technique for representing the knowledge base obtained in a particular scheme or diagram so that the relationship or connection between data and other data can be known. In this study, knowledge representation is a rule table with evidence value from an expert. After that, the next stage is the withdrawal of reasoning using the inference engine. This study uses the Forward Chaining and Certainty Factor as an inference engine. There are two kinds of certainty factors that are used (Alfiah et al., 2019; Pamungkas et al., 2021), the first is the certainty factor which is filled in by the expert along with the rules. The second is the certainty factor given by the user. The process of calculating the percentage of confidence begins with rules that have a single symptom. Then each new rule calculates its CF value using Equation 1 below.

$$CF = CF_{user} * CF_{pakar} \dots \dots \dots (1)$$

The rules of the Certainty Factor method are as follows (Putra & Yuhandri, 2021; Rahmadhani et al., 2020; Ramadhan & Sitorus Pane, 2018; Sholeha et al., 2023; Sukiakhy et al., 2022).

First, the rules for adding two positive Certainty Factor factors use equation 2.

$$(CF_a CF_b) = CF_a + CF_b * (1 - CF_a) \dots \dots \dots (2)$$

The second is rules for adding two negative Certainty Factors use equation 3.

$$(CF_c CF_d) = CF_c + CF_d + (CF_c * CF_d) \dots \dots \dots (3)$$

The third is rules for adding positive Certainty Factors and negative certainty factors are more complex using equation 4.

$$(CF_e CF_f) = \frac{CF_e + CF_f}{1 - (|CF_e|, |CF_f|)} \dots \dots \dots (4)$$

C. System Development

In this study, system development uses the System Development Life Cycle method with modelling using use case diagrams in the Unified Modeling Language (UML). In the UML method, use cases are used to describe system requirements and how users can interact with the system. While the Activity diagram describes a series of flows from user activity (users) and the system. Class diagrams describe the types of objects in the system and the various kinds of static relationships between them. Sequence diagrams are used to describe the dynamic behaviour of the system that occurs between objects or entities.

D. System Testing

The final stage in the research is to test the system. In this research, system testing is divided into two scenarios. First testing using Black Box Testing is carried out to test the functionality of the features in this expert system. The second is testing the level of accuracy of the expert system that has been developed. Testing the level of accuracy is carried out by conducting several test scenarios to find out the output produced by the expert system following the validation of an expert.

RESULTS AND DISCUSSION

In this section, the overall results obtained from this research will be discussed, especially in terms of the expert system developed based on the stages that have been carried out.

A. Data Acquisition

The data in this study focused only on the types of disorders most commonly experienced in today's society. The types of mental illness disorders found in this expert system are described in Table 1. In addition, the disease data obtained has also been

validated by an expert; in this study, the expert was a psychologist at a hospital in Yogyakarta.

Table 1. List of Mental Illnesses

Code	Mentall illness
P01	Anxiety Disorder
P02	Skizofrenia
P03	Mood Disorder
P04	Autism
P05	Attention deficit hyperactivity disorder
P06	Depression

In addition, it is also equipped with data on symptoms of mental illness. The types of mental illness symptoms found in this expert system are described in Table 2. In addition, the symptom data obtained has also been validated by an expert; where in this study, the expert was a psychologist at a hospital in Yogyakarta.

Table 2. List of Mental Illnesses Symptoms

Code	Symptoms
G01	Fear of a specific phobia or fear of an object
G02	Anxiety in every situation
G03	Social anxiety
G04	Obsessive-compulsive disorder
G05	Panic attacks
G06	Feeling worried
G07	Post-traumatic stress disorder
G08	Talking over and over to yourself
G09	Avoiding social contact
G10	Talking and seeing things that are not there
G11	Problems with memory and reasoning
G12	Depression and lack of emotion
G13	Have no attention
G14	Get bored quickly with routine
G15	Very active and cannot stay still
G16	Cannot concentrate or focus
G17	Talking and not listening
G18	Touching and playing with everything
G19	Talking without thinking and acting emotionally
G20	Feeling like being alone
G21	Difficulty in speaking
G22	Strange body movements and patterns
G23	Indifference and lack of emotion towards objects, people and events
G24	Lack of confidence
G25	Difficulty adapting to other people
G26	Loss of energy
G27	Changes in appetite
G28	Sleep disorders
G29	Feeling anxious
G30	Inability to make decisions
G31	Feeling uneasy
G32	Feeling useless
G33	Feeling guilty or hopeless
G34	Thinking about self-harm/suicide

B. Knowledge Representation and Inference Engine

An expert system that applies the certainty factor calculation method takes several rules or

rules and the weight of the CF value given by the expert. The rules in this study are made in the form of IF-THEN (if-then) equipped with expert CF values. CF values are required for each symptom in each disorder. Experts provide a CF value scale for each symptom between 0.2 – 1.0 according to the expert's belief in the symptoms of a particular disorder. The rules containing the symptoms and expert CF values for each disorder are shown in Table 3 below.

Table 3. Rules Based of Mental Illnesses

No	Rules	CF Expert
1	<i>IF is afraid of a specific phobia or object</i> <i>THEN Anxiety Disorder</i>	0.5
2	<i>IF anxiety in every situation</i> <i>THEN Anxiety Disorder</i>	0.5
3	<i>IF social anxiety</i> <i>THEN Anxiety Disorder</i>	0.3
4	<i>IF obsessive-compulsive disorder</i> <i>THEN Anxiety Disorder</i>	0.3
5	<i>IF panic attacks</i> <i>THEN Anxiety Disorder</i>	0.5
6	<i>IF is worried</i> <i>THEN Anxiety Disorder</i>	0.4
7	<i>IF post-traumatic stress disorder</i> <i>THEN Anxiety Disorder</i>	0.4
8	<i>IF avoids social contact</i> <i>THEN Anxiety Disorder</i>	0.4
9	<i>IF feels like being alone</i> <i>THEN Anxiety Disorder</i>	0.3
10	<i>IF lack of self-confidence</i> <i>THEN Anxiety Disorder</i>	0.2
11	<i>IF finds it difficult to adapt to other children</i> <i>THEN Anxiety Disorder</i>	0.6
12	<i>IF speaks repeatedly for itself</i> <i>THEN Schizophrenia</i>	0.5
13	<i>IF avoids social contact</i> <i>THEN Schizophrenia</i>	0.4
14	<i>IF speaks and sees things that are not there</i> <i>THEN Schizophrenia</i>	0.3
15	<i>IF has problems with memory and reasoning</i> <i>THEN Schizophrenia</i>	0.2
16	<i>IF depression and lack of emotion</i> <i>THEN Schizophrenia</i>	0.3
17	<i>IF has no concerns</i> <i>THEN Schizophrenia</i>	0.3
18	<i>IF has problems with memory and reasoning</i> <i>THEN Mood Disorders</i>	0.6
19	<i>IF depression and lack of emotion</i> <i>THEN Mood Disorders</i>	0.2
20	<i>IF has no concerns</i> <i>THEN Mood Disorders</i>	0.5
21	<i>IF quickly gets bored with routine</i> <i>THEN Mood Disorders</i>	0.4
22	<i>IF lack of self-confidence</i> <i>THEN Mood Disorders</i>	0.3

No	Rules	CF Expert
23	IF has difficulty adapting to other people THEN Mood Disorders	0.5
24	IF speaks without thinking and acts emotionally THEN Autism	0.5
25	IF feels like being alone THEN Autism	0.6
26	IF has difficulty speaking THEN Autism	0.3
27	IF Strange body movements and patterns THEN Autism	0.2
28	IF indifference and lack of emotion towards objects, people and events THEN Autism	0.2
29	IF lack of self-confidence THEN Autism	0.5
30	IF finds it difficult to adapt to other children THEN Autism	0.4
31	IF speaks repeatedly for itself THEN ADHD	0.5
32	IF speaks and sees things that are not there THEN ADHD	0.4
33	IF has problems with memory and reasoning THEN ADHD	0.5
34	IF quickly gets bored with activities THEN ADHD	0.4
35	IF is very active and can't stay still THEN ADHD	0.2
36	IF cannot concentrate or focus THEN ADHD	0.3
37	IF talks all the time and can't listen THEN ADHD	0.4
38	IF touches and plays with everything THEN ADHD	0.5
39	IF speaks without thinking and acts emotionally THEN ADHD	0.3
40	IF cannot concentrate or focus THEN Depression	0.5
41	IF loses energy THEN Depression	0.5
42	IF changes in appetite THEN Depression	0.4
43	IF sleep disorders THEN Depression	0.3
44	IF feels anxious THEN Depression	0.2
45	IF inability to make decisions THEN Depression	0.2
46	IF feels uneasy THEN Depression	0.2
47	IF feels useless THEN Depression	0.1
48	IF feels guilty or hopeless THEN Depression	0.3
49	IF thinks about self-harm/suicide THEN Depression	0.6

After the production rules are made, the next step is to conduct a diagnostic experiment to ensure that the inference engine used works correctly. The inference engine used is Forward Chaining combined with Certainty Factor. To better understand the process of calculating this system, the following is an example of a case in performing manual calculations using the Forward Chaining and Certainty Factor methods.

For example, there has been a man for some time recently who has felt that he has a mental health disorder. The symptoms he is feeling are as follows.

- 1) Not being able to concentrate and focus is a symptom of ADHD (P05) and Depression (P06)
- 2) Changes in appetite are a symptom of depression (P06)
- 3) Feeling uneasy is a symptom of depression (P06)
- 4) Feeling useless is a symptom of Depression (P06)
- 5) Feeling guilty or hopeless is a symptom of depression (P06)

So for diagnostic calculations using Forward Chaining and the Certainty Factor is as follows.

1) ADHD (P05)
 Cannot concentrate and focus (G36) [CFexpert = 0.3 || CFuser = 0.6]
 $CF(G36) = CFuser * CFexpert = 0.6 * 0.3 = \mathbf{0.18}$

2) Depression (P06)
 Cannot concentrate and focus (G40) [CFexpert = 0.5 || CFUser = 0.6]
 $CF(G40) = CFuser * CFexpert = 0.6 * 0.5 = \mathbf{0.3}$

Changes in appetite (G42) [CFpakar = 0.4 || CFuser = 0.2]
 $CF(G42) = CFuser * CFexpert = 0.2 * 0.4 = \mathbf{0.8}$

Feeling uneasy (G46) [CFexpert = 0.2 || CFuser = 0.6]
 $CF(G46) = CFuser * CFexpert = 0.6 * 0.2 = \mathbf{0.12}$

Feeling useless (G47) [CFexpert = 0.1 || CFuser = 0.6]
 $CF(G47) = CFuser * CFexpert = 0.6 * 0.1 = \mathbf{0.6}$

Feeling guilty or hopeless (G48) [CFexpert = 0.3 || CFuser = 0.2]
 $CF(G48) = CFuser * CFexpert = 0.2 * 0.3 = \mathbf{0.6}$

Then calculate it using CF Combination

$$\begin{aligned}
 \mathbf{CF Comb} &= CFa + CFb * (1 - CFa) \\
 &= 0.3 + 0.8 * (1 - 0.3) \\
 &= 0.3 + 0.8 * (0.7) \\
 &= 0.3 + 0.56 \\
 &= \mathbf{0.86} \\
 &= 0.86 + 0.12 * (1 - 0.86)
 \end{aligned}$$

$$\begin{aligned}
 &= 0.86 + 0.12 * (0.14) \\
 &= 0.86 + 0.0168 \\
 &= \mathbf{0.8768} \\
 &= 0.8768 + 0.6 * (1 - 0.8768) \\
 &= 0.8768 + 0.6 * (0.1232) \\
 &= 0.8768 + 0.07392 \\
 &= \mathbf{0.95072} \\
 &= 0.95072 + 0.6 * (1 - 0.95072) \\
 &= 0.95072 + 0.6 * (0.04928) \\
 &= 0.95072 + 0.029568 \\
 &= \mathbf{0.980288}
 \end{aligned}$$

Based on the above calculations, it can be seen that the results of the diagnosis with the highest level of confidence in the type of mental illness suffered by a man are depression, with a CF value percentage of 98%.

C. System Development

In system development, the interface implementation stage is one of the essential stages in meeting user needs in interacting with the system created. Good interface facilities will significantly assist the user in understanding the processes being carried out by the system to improve system performance. In this section, two primary feature interfaces will be displayed on the system that has been built, namely the diagnosis page interface and the diagnostic results page interface.

On the diagnosis interface page containing the selection of symptoms and conditions, the user must select the conditions that match what he is suffering from to carry out system processes. The details of the diagnostic page interface can be seen in Figure 2.

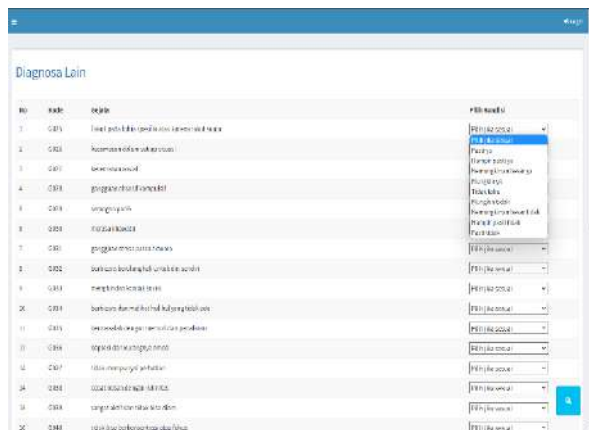


Figure 2. The Diagnostic Page Interface

While the results of the diagnosis display the results of the symptoms that have been selected in the form of CF and % (per cent) values, descriptions, pictures and suggestions for handling the disorder, details of the interface for the diagnosis results page, can be seen in Figure 3.



Figure 3. The Diagnostic Results Page Interface

D. System Testing

The final stage in the research is system testing. In this work, system testing is divided into two scenarios. First testing using Black Box Testing is carried out to test the functionality of the features in this expert system. Following Table 4 is the results of Black Box testing.

Table 4. Black Box Testing Results

No	Features	Scenarios	Results
1	Admin Login	Enter the registered username and password	Valid.
		Entering an unregistered username and password	Valid.
2	Nuisance Data	Enter fault data	Valid.
		Editing fault data	Valid.
		Delete tampering data	Valid.
3	Symptoms Data	Enter symptom data	Valid.
		Edit symptom data	Valid.
		Delete symptom data	Valid.
4	Knowledge Data	Input knowledge data	Valid.
		Edit knowledge data	Valid.
		Deleting knowledge data	Valid.
5	Admin	Enter admin data	Valid.
		Edit admin data	Valid.
		Delete admin data	Valid.
6	Logout	Pressing the logout button	Valid.
7	Diagnosis	Choose the condition of the symptoms you are experiencing, then click the process button	Valid.

Based on the tests carried out, overall, the features contained in this expert system have been running well. This is shown in Table 3, with no errors in all the test scenarios performed.

The second is testing the level of accuracy of the expert system that has been developed. Testing the

level of accuracy is carried out by conducting several test scenarios to find out the output produced by the expert system following the validation of an expert. The following Table 5 is an example of an expert system accuracy testing scenario that has been developed.

Table 5. Accuracy Testing Scenario

No	Symptoms	System	Expert	Results
1	a. Problems with memory and reasoning			
	b. Depression and lack of emotion			
	c. Has no attention			
	d. Get bored quickly with routine	Mood Disorder 99%	Mood Disorder	Valid
	e. Lack of self-confidence			
	f. Difficulty adapting to other children			
	g. Difficulty adapting to other children			
2	a. Speak without thinking and act emotionally			
	b. Feel like you want to be alone			
	c. Difficulty in speaking			
	d. Strange body movements and patterns	Autism 97%	Autism	Valid
	e. Indifference and lack of emotion towards objects, people and events			
	f. Lack of self-confidence			
	g. Difficulty adapting to other children			

Accuracy testing aims to determine the performance of the expert system in providing the results of a diagnosis of a type of mental illness. At this stage, there are 49 cases with various symptoms and diseases to test the accuracy of expert analysis values, which will be compared with the actual expert system results. Based on the tests carried out from a total of 49 cases tested, 47 of them had a concordance between the system diagnosis and the expert diagnosis. Meanwhile, in the other 2 cases, there were still differences between system and expert diagnoses. Then the accuracy value of this expert system can be calculated using the following equation 5.

$$Accuracy = \frac{True\ Diagnosis\ Data}{All\ Diagnosis\ Data} * 100\%.....(5)$$

$$Accuracy = \frac{47}{49} * 100\%$$

$$Accuracy = 95,918 \%$$

Based on the test results, it can be concluded that the percentage accuracy value from the comparison results of expert systems for diagnosing mental illness types with the forward chaining method and the certainty factor has a value of 95,918%.

CONCLUSION

Based on the research results of the expert system for diagnosing mental illness using Forward Chaining and the Certainty Factor Method, the conclusions are drawn as follows. First, the expert-based system that has been developed can help provide the results of a diagnosis that is carried out before there are complaints and will be detected early by efforts to increase awareness of the prevention of mental illness and reduce the tendency to self-diagnose. Second, applying the forward chaining method and certainty factor to this expert system can produce an accuracy rate of 95.918%. An expert has also validated these results; in this study, the expert was a psychologist at a hospital in Yogyakarta. The suggestion for further research is to form a more accurate knowledge base by adding data on symptoms and disorders from various experts to produce a better diagnosis process.

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ANALYSIS OF USABILITY USING HEURISTIC EVALUATION METHOD AND MEASUREMENT OF SUS ON PRICILIA APPLICATION

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Abstract— *The Presence Digital Application (PRICILIA) is a presence application owned by PT. BGR Logistics Indonesia. However, until now, there has never been an evaluation of usability testing. Complaints from users regarding the PRICILIA application include menu displays that are less interactive, long loading times, and the unavailability of other alternatives besides GPS. Of course, this affects the level of user satisfaction with the application. Therefore, usability testing is needed to be able to measure the level of user comfort, application feasibility, and the application interface. In this study, the system evaluation method used is Heuristic Evaluation with measurement using the System Usability Scale (SUS). The results of this study indicate that aspects that need to be improved with high priority are Error Prevention (H5) and Recognition rather than Recall (H6) because they have a seriousness rating on a scale of 3, while the average score of the final seriousness rating obtained from a total of 10 heuristic aspects is 1,72 which is then rounded off to a scale of 2. The SUS test results obtained an average final SUS score of 55.13. The results of the calculation of the SUS method are that the Acceptance Ranges have low marginal status, the Grade Scale is on a D scale, and the Adjective Twigs are at the OK level. This shows that the PRICILIA application still needs improvement. Therefore, 30 recommendations for improvement are proposed for future application development.*

Keywords: *heuristic evaluation, presence application, system usability scale (SUS), usability analysis.*

Intisari— *Presence Digital Application (PRICILIA) merupakan aplikasi presensi yang dimiliki oleh PT. BGR Logistik Indonesia. Namun sampai dengan saat ini belum pernah diadakan evaluasi usability testing. Keluhan dari para pengguna terkait aplikasi PRICILIA meliputi tampilan menu yang kurang*

interaktif, durasi waktu loading yang cukup lama, serta belum tersedianya alternatif lain selain presensi dengan GPS. Tentu hal ini mempengaruhi tingkat kepuasan pengguna terhadap aplikasi. Oleh karena itu usability testing diperlukan untuk dapat mengukur tingkat kenyamanan user, kelayakan aplikasi, dan interface aplikasi. Dalam penelitian ini metode evaluasi sistem yang digunakan yaitu Heuristic Evaluation dengan pengukurannya yaitu menggunakan System Usability Scale (SUS). Hasil dari penelitian ini aspek yang perlu diperbaiki dengan prioritas tinggi adalah Error Prevention (H5) dan Recognition Rather Than Recall (H6) karena memiliki severity ratings pada skala 3, sedangkan untuk rata-rata skor severity ratings akhir yang didapat dari total keseluruhan 10 aspek heuristik yaitu sebesar 1,72 yang kemudian dibulatkan menjadi skala 2. Hasil dari pengujian SUS didapatkan skor rata-rata akhir SUS sebesar 55,13. Hasil perhitungan metode SUS tersebut yaitu Acceptability Ranges berstatus marginal low, Grade Scale berada di skala D, serta Adjective Ranting berada diposisi tingkat OK. Hal ini menunjukkan bahwa aplikasi PRICILIA masih membutuhkan perbaikan. Oleh karena itu dalam penelitian ini diusulkan 30 rekomendasi perbaikan untuk pengembangan aplikasi kedepannya.

Kata kunci: *heuristic evaluation, aplikasi presensi, system usability scale (SUS), analisis usability.*

INTRODUCTION

The development of information technology (IT) is very important for companies or agencies facing the current era of globalization. By utilizing IT, companies can increase efficiency and productivity in managing information, including human resource information (Pribadi & Setiyawati, 2021). In a situation where the company has a

cooperative relationship with other companies out of town and needs to send its employees to other places, the problem of absenteeism is one of the things that needs attention (Gunawan et al., 2022).

The Presence Digital Application (PRICILIA) is an application owned by PT. BGR Logistik Indonesia that functions as a medium for digital attendance and manages incoming and outgoing data as well as employee work hours. However, due to the absence of available information regarding effectiveness, efficiency, and user satisfaction, This becomes an obstacle in determining future application development steps. (Munawar et al., 2023).

In previous research, specifically in the usability analysis of the SIAM academic information system application at the University of Muhammadiyah Riau (UMRI), several issues were identified. These issues included user experience problems, misconceptions, inconsistencies, non-functional navigation links, and unresponsive displays. Furthermore, it was noted that SIAM had never been assessed using specific methods or standards, which in turn had an impact on user satisfaction levels. Therefore, it was deemed necessary to evaluate the interface design for the student application, using the Heuristic Evaluation method. The research findings revealed that the lowest percentages with "Fairly Good" and "Not Good" qualifications were found in variables H3 (P8), H4 (P9, P10, and P11), H6 (P13 and P14), H7 (P16), H8 (P17), and H10 (P22). Based on the recommendations derived from these results, the focus for improvements was primarily placed on variable H4, which had the highest frequency of problems, while variable H7 (P16) had the lowest percentage at 23%, indicating a "Not Good" rating. This research also generated solutions in the form of recommendations that can be used as a reference for the SIAM development team in making usability improvements to SIAM (Ahsyar et al., 2019).

In the evaluation study of the Ezyschool application, the Heuristic Evaluation and Human-Centered Design methods were employed. The evaluation aimed to assess the extent of user experience (UX) success in meeting user needs and satisfaction. The Ezyschool application is used to manage student activities, including daily or monthly attendance, financial information and payments, student exam grades, and more. The research had two main objectives. First, to identify usability issues using heuristic principles, and second, to design solutions based on feedback from evaluators, severity ratings, and Google Material Design guidelines. The results of this study show a comparison between the initial evaluation findings and the design solutions, which led to a better UX design. This improvement resulted in a reduction of

10 heuristic problems, leaving only 7 issues in the design solution (Arifin et al., 2019).

In a previous study conducted at PT SEVINA, the usability analysis of the mobile application Edlink was performed using the Heuristic Evaluation method. Several issues were identified within this application, including the inability to connect to the server, the inability to click the submit button for quizzes, and the inability to upload assignments. These issues significantly impacted user satisfaction levels. The results of the research yielded 38 recommendations for improvement, primarily focusing on functionality and information related to disaster and major issue categories. These recommendations can be utilized to enhance the usability of the Edlink mobile application in the future (Fatihahsari & Darujati, 2021).

In a subsequent study conducted on the Tim Kita application at the Central Statistics Agency (Badan Pusat Statistik) of Indramayu Regency, the researchers employed the system evaluation methods of Heuristic Evaluation and SUS (System Usability Scale). The Tim Kita application is used for online attendance and work reporting by data processing officers at the Indramayu Regency BPS. The research was conducted to evaluate the usability of the Tim Kita application from the perspectives of effectiveness, efficiency, and user satisfaction based on heuristic principles. The testing results revealed that the effectiveness level was 80%, efficiency was 61.65%, and user satisfaction was 60%, with ratings of "OK" and a grade scale of "D." This indicates that while the Tim Kita application meets user needs, its usage is not yet optimal. This research provides insights into usability issues with the Tim Kita application and offers recommendations for future improvements (Prayitno, 2022).

The PRICILIA application has been developed since 2019. However, until now there has never been a usability testing evaluation to measure the user experience of the application's user interface. Complaints from users regarding the PRICILIA application include a menu display that is less interactive, the duration of the loading time for taking attendance coordinates is quite long, there is no alternative other than presence with GPS in the application, resetting the device, and the user's unique password, which can only be done through the admin system. Of course, this affects the level of user satisfaction with the application. Therefore, usability testing is needed to be able to measure the level of user comfort, application feasibility, and the application interface.

The purpose of this research is to evaluate the application of PRICILIA attendance at PT. BGR Logistik Indonesia to determine the level of user

comfort, application feasibility, and the application interface using the heuristic evaluation research method.

Evaluation is an ongoing and regular process that aims to collect, interpret, and provide information about a program. This information is used as a basis for decision making, policy making, or the planning of subsequent programs (Akhsani et al., 2020).

Usability is a science that focuses on analyzing and testing the ease of use of software. The goal is to make the application easy for users to use and increase the effectiveness and efficiency of its use (Ependi et al., 2019).

Heuristic evaluation is a usability engineering technique used to identify usability problems in user interface design. This method involves a number of evaluators to evaluate the user interface and assess the suitability of the design against usability principles (Pertiwi et al., 2019).

With the usability analysis using the heuristic evaluation method, it is hoped that we can find out what the usability problems are in the PRICILIA application both in terms of user interface design and user experience so that recommendations or improvements to the application can be produced based on the evaluation results.

In the previous study, which was conducted by Edlink, the results of the evaluation by three expert evaluators revealed that the current condition of the application has 84 identified issues. The most prevalent usability issues were found in principle H1 - Visibility of System Status, accounting for 23.8% of the total 82 issues, with an average severity rating of 2.5. Meanwhile, the highest average severity rating of 3.22 was observed in principle H3 - User Control and Freedom out of a total of 3 identified issues. The researcher provided 38 recommendations for improvements that can be utilized in the development of Edlink.

In this research, a total of 105 issues were identified in the PRICILIA application. The most frequently encountered issues in the Heuristic Evaluation principles were in the aspect of User Control and Freedom (H3) with a total of 8 identified issues (18%), followed by Match between the System and the Real World (H2) and Flexibility and Efficiency of Use (H7), each with a total of 7 identified issues (16%). However, the aspects that require significant improvement are Error Prevention and Recognition Rather Than Recall, as they received severity ratings of 3, which means they fall into the category of major usability issues that need immediate attention. Therefore, in this research, 30 proposed improvement recommendations have been developed for future application development.

MATERIALS AND METHODS

1. Research Stages

The following are the stages of the research conducted in analyzing the PRICILIA application.

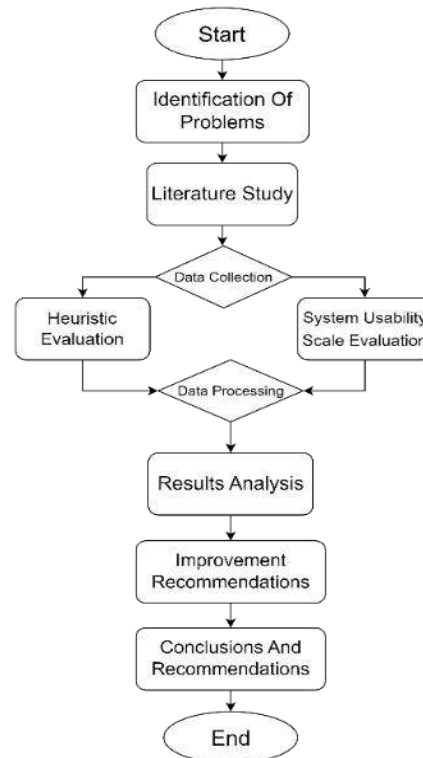


Figure 1. Research Flow

Based on Figure 1, it can be understood that the stages of this research include:

1. Problem Identification

The problem identification stage is carried out to obtain results that are in accordance with the research objectives. After identifying the problem, the problem is described in the form of a problem statement. The formulation of the problem in this study is how to measure the usability of the PRICILIA application using the heuristic evaluation method.

2. Literature Study

At this stage, a literature study is carried out by reading, studying, and recording important information related to the problem being discussed so that it can support research. The sources used in this literature study include journals, ebooks, and articles related to usability.

3. Data Collection

Data collection for this research involved observing at PT BGR Logistik Indonesia Jakarta, conducting interviews with users and application developers for reviewing application

enhancements, and distributing questionnaires to active PRICILIA application users via WhatsApp groups with Google Forms.

a. **Heuristic evaluation**

In the heuristic evaluation method, the measurement scale used is severity ratings. The following classification of severity ratings (Ependi, 2019) can be seen in Table 1.

Table 1. Classification of severity ratings

Severity ratings	Description
0	Don't Agree : I don't agree that this is a usability problem at all.
1	Cosmetic : Need not be fixed unless extra time is available on project.
2	Minor : Fixing this should be given low priority.
3	Major : Important to fix, so should be given high priority.
4	Catastrophic : Imperative to fix this before product can be released.

The PRICILIA application evaluation process uses the heuristic evaluation method with the aim of identifying existing problems with the application. Heuristic evaluation is a process of examining or inspecting usability carried out by evaluators who are experts in the field of usability (Wibowo, 2020). An evaluator is someone who has knowledge and understanding of heuristics and has experience using various interfaces. The evaluator's job is to observe and evaluate the system being assessed by identifying errors in the system and providing input to researchers, who then change ideas for application developers (Ependi, 2019). In this study, 3 evaluators were selected to assess the PRICILIA application user interface.

The evaluation was carried out using 10 heuristic evaluation principles developed by Nielsen. The following are 10 heuristic evaluation principles (Ependi, 2019), which can be seen in Table 2.

Table 2. Principles of Heuristic Evaluation

Usability Aspect	Description
Visibility of System Status	Shows the status of the system.
Match Between System and The Real World	The use of designs/objects that correspond to the real world.
User Control and Freedom	User freedom and control over the system.
Consistency and Standart	Up to standard and has consistency.
Error Prevention	Provides user error prevention facilities.

Recognition Rather than Recall	Makes it easier for users to recognize the system than to remember the system.
Flexibility and Efficiency of Use	Having a flexible process in every action so that it can serve both experienced and inexperienced users.
Aesthetic and Minimalist Design	It has an aesthetic and simple design.
Help Users Recognize, Diagnose, and Recover from Errors	Assist the user in recognizing and escaping an action error.
Help and Documentation	Help the user complete an action that is not yet understood.

b. **System usability scale (SUS)**

Assessment with the System Usability Scale (SUS) is carried out by giving a questionnaire consisting of 10 questions to PRICILIA application users (Diah Indrayani et al., 2022). This is done to determine the level of user satisfaction by using a Likert scale from 1 to 5 as the answer choices. The following Likert scale scores can be seen in Table 3.

Table 3. SUS Likert scale scores

Answers	Scores
Strongly Disagree (STS)	1
Disagree (TS)	2
Doubtful (RG)	3
Agree (S)	4
Strongly Agree (SS)	5

The following is a list of System Usability Scale (SUS) questions that will be given to respondents using the PRICILIA application, which can be seen in Table 4.

Table 4. List of SUS Questionnaire Questions

No	Question	Scale
1	I feel that using the PRICILIA app is easy.	1 to 5
2	I find this system complicated to use.	1 to 5
3	I feel that the features of the PRICILIA application work as they should.	1 to 5
4	I feel that the PRICILIA app has a lot of unnecessary features.	1 to 5
5	I need help from other people or technicians in using this system.	1 to 5
6	I found the PRICILIA app easy to use once I got used to it.	1 to 5
7	I feel that I need to learn many things before I can use the PRICILIA application.	1 to 5
8	I find the navigation within the PRICILIA app confusing.	1 to 5
9	I feel that the PRICILIA application has an attractive appearance.	1 to 5
10	I feel that I can use the PRICILIA application smoothly.	1 to 5

c. Population and Sample

A population is a generalized area consisting of objects or subjects who have certain qualities and characteristics determined by the researcher to be studied and then drawn conclusions from (Firmansyah & Dede, 2022). The population in this study includes all users of the PRICILIA application at PT. BGR Logistics Indonesia in Jakarta, which has 212 users.

While the sample is part of the number and characteristics possessed by a population, in taking the sample, one must use a certain method based on certain considerations (I Ketut Swarjana, 2022). Determination of the number of samples in this study is determined by the Roscoe method. The Roscoe method involves determining the number of samples by 10 times the number of variables studied (Agi & Nurjannah, 2022). Based on this, the number of samples in this study, namely as many as 100 respondents, was determined based on 10 multiplied by 10 variables in the study. The following characteristics of the respondents in this study can be seen in Table 5.

Table 5. Respondent Criteria

No.	Criteria
1.	Gender 1) Male 2) Female
2.	Age 1) 18-25 Years Old 2) 26-40 Years Old 3) >40 Years Old

4. Data Processing

At this data processing stage, the calculation of the results of the questionnaire that have been obtained is carried out according to the formula from Heuristics and SUS.

a) Calculation of heuristic evaluation values

The heuristic evaluation value is obtained by calculating the formula (Wibowo, 2020):

$$\sum Hx = 0 * x + 1 * x + 2 * x + 3 * x + 4 * x \dots \dots \dots (1)$$

Description:

$\sum Hx$ = The sum of the rating scores of the heuristic sub-aspects in each heuristic aspect (H1, H2.....H10).

x = Usability points, worth 1/0.

Then, to generate the severity rating value of each heuristic aspect, use the formula:

$$Sv = \sum \frac{Hx}{n} \dots \dots \dots (2)$$

Description:

Sv = Severity rating results in one heuristic aspect
 n = the number of heuristic sub-aspects in each heuristic aspect.

b) Calculation of SUS value

There are rules for determining the final value of the System Usability Scale (SUS) questionnaire results, which are as follows (Diah Indrayani et al., 2022):

1) Odd statements, namely: 1, 3, 5, 7, and 9 scores given by respondents minus the 1.

$$\text{Odd SUS score} = \sum Px - 1 \dots \dots \dots (3)$$

Where Px is the odd number of questions.

2) Even statements, namely 2, 4, 6, 8, and 10 scores given by respondents are used to reduce 5.

$$\text{even SUS score} = \sum 5 - Pn \dots \dots \dots (4)$$

Where Pn is the number of even questions.

3) The results of the conversion are then added up for each respondent and multiplied by 2.5 to get a value range between 0 - 100.

$$(\sum \text{skor ganjil} - \sum \text{skor genap}) \times 2,5 \dots \dots \dots (5)$$

4) After the score of each respondent is known, the next step is to find the average score by adding up all the scores and dividing it by the number of respondents. This calculation can be seen in the following formula:

$$\bar{x} = \frac{\sum x}{n} \dots \dots \dots (6)$$

Where \bar{x} is the average score, $\sum x$ is the total score of the System Usability Scale and n is the number of respondents.

From these results, an average value will be obtained from all the assessments of the respondent's score. The following determines the grade based on the assessment results obtained (Diah Indrayani et al., 2022), which can be seen in Table 6.

Table 6. Grade SUS scores

Grade	SUS Score
A	score >= 80.3
B	score >= 74 and < 80.3
C	score >= 68 and < 74
D	score >= 51 and < 68
F	score more < 51

5. Analysis of Results

After the data processing stages are carried out, the next stage is data analysis. This stage begins by combining the problems identified by the three expert evaluators by filling out a questionnaire. Then a process of consolidation, or filling in the severity rating, is carried out by interviewing each evaluator according to the combined results of the problems of the three evaluators. The researcher then calculates the average severity rating to determine the priority of repairs.

In analyzing the results of the previous SUS method, validation and reliability tests were first carried out to ensure that the respondents' results

were valid and confirmed that they could be used for calculations using the SUS method formula (Janna & Herianto, 2021). Testing the validity and reliability is done with data analysis tools using SPSS software version 25.

6. Conclusions and Suggestions

After completing all stages, the last stage is to draw conclusions from the results that have been obtained and provide suggestions based on the findings of the research that has been conducted to make improvements to the system. Recommendations for improvements proposed after conducting an evaluation with a heuristic evaluation and SUS calculation aim to improve the usability aspect and reduce the possibility of problems occurring in the application.

RESULTS AND DISCUSSION

A. Heuristic Evaluation Results

Heuristic Evaluation testing was carried out by involving 3 evaluators. The following criteria for the selected evaluators can be seen in Table 7.

Table 7. Evaluator Criteria

No.	Kriteria Evaluator
1	Minimum bachelor's degree
2	Understand the concept of interface design as a usability expert or Human Computer Interaction.
3	Was a mobile application developer

Following are the results of testing with the heuristic evaluation method, which can be seen in Table 8.

Table 8. Heuristic Evaluation Test Results

Usability Aspect	Average Severity Rating	Value Rounding Scale 0-4
H1	1,7	2
H2	2,4	2
H3	2,3	2
H4	0	0
H5	2,6	3
H6	2,5	3
H7	2,3	2
H8	1	1
H9	1,3	1
H10	1,1	1
Severity rating average value	1,72	2

Based on the evaluation results with the heuristic evaluation, the average final severity rating score obtained is a scale of 2. This shows that the PRICILIA application requires improvement. The following details the usability problem from the

evaluation results based on the 10 heuristic evaluation principles, which can be seen in Table 9.

Table 9. Heuristic Evaluation Results

Code	Usability Aspect	Evaluation result	Category & Description
H1	Visibility of system status	Scale 2	Minor usability problem (given low priority for improvement)
H2	Match between system and the real world	Scale 2	Minor usability problem (given low priority for improvement)
H3	User Control and Freedom	Scale 2	Minor usability problem (given low priority for improvement)
H4	Consistency and standards	Scale 0	No usability issues
H5	Error Prevention	Scale 3	Major usability problem (given high priority for improvement)
H6	Recognition rather than recall	Scale 3	Major usability problem (given high priority for improvement)
H7	Flexibility and efficiency of use	Scale 2	Minor usability problem (given low priority for improvement)
H8	Aesthetic and minimalist design	Scale 1	Cosmetic usability problem (no need to fix unless extra time is available).
H9	Help users recognize, diagnose, and recover from errors	Scale 1	Cosmetic usability problem (no need to fix unless extra time is available).
H10	Help and documentation	Scale 1	Cosmetic usability problem (no need to fix unless extra time is available).

Based on the analysis conducted, it was found that the aspects that need to be improved significantly are Error Prevention and Recognition Rather Than Recall, compared to other usability aspects. The scores obtained for the Error

Prevention and Recognition Rather Than Recall aspects are 3 each, which fall into the category of major usability problems.

Apart from the Error Prevention and Recognition Rather Than Recall aspects, there are also other usability aspects that need attention, namely Visibility Of System Status, Match Between System And The Real World, User Control And Freedom, and Flexibility and Efficiency Of Use. However, the level of improvement for this aspect is lower because it gets a score of 2, which is included in the category of minor usability problems.

Aspects of usability with codes H8, H9, and H10 get a score of 1, which is included in the category of cosmetic problems. Improvements to these aspects can be made if there is additional time to refine the interface, but they are not a top priority.

Meanwhile, the Consistency and Standards (H4) aspect gets a score of 0, this indicates that the designed interface is in accordance with the Heuristic Evaluation principles and there are no significant problems based on the evaluation using this method.

B. Results of the System Usability Scale (SUS)

Before calculating the SUS formula, the results of the SUS respondents' responses will be tested for validity and reliability first with SPSS software version 25. Following are the results of testing the validity test with SPSS, as seen in Table 10.

Table 10. Validity Test Results

Question	Correlation Value (RCount)	RTable	Description
X1	0,325	0,1966	Valid
X2	0,524	0,1966	Valid
X3	0,468	0,1966	Valid
X4	0,563	0,1966	Valid
X5	0,532	0,1966	Valid
X6	0,354	0,1966	Valid
X7	0,405	0,1966	Valid
X8	0,574	0,1966	Valid
X9	0,588	0,1966	Valid
X10	0,626	0,1966	Valid

The validity test of the questionnaire can be considered valid if the value of Rcount > Rtable, and the purpose of the validity test is to ensure the accuracy and precision of the measurements used in the measuring instrument (Janna & Herianto, 2021). The significance level used is **0.05** with a value of r in the table of 100 respondents, namely **0.1966**.

Based on the results of validity testing with SPSS software, the published questionnaire results are **valid**. This can be proven, namely from the test results, which show **rcount > rtable**.

Furthermore, reliability testing was carried out with SPSS software to determine the level of consistency of measurement results. The following are the results of the reliability test with SPSS, which can be seen in Table 11.

Table 11. Reliability Test Results

Cronbach's Alpha	N of items	Description
0,657	10	Reliable

The Cronbach alpha (CA) reliability test is declared valid for **reliability** if the Cronbach alpha value is > **0.60**.

Based on the results of the reliability test above, the variable user satisfaction with the application is declared reliable because the number of Cronbach alpha is > 0.60. The Cronbach alpha variable value obtained is 0.657. So it can be seen that the research variable is reliable.

The calculation of the System Usability Scale (SUS) is carried out according to the formula above. The following results of the SUS calculation can be seen in Table 12.

Table 12. SUS Calculation Results

R	Questionnaire										The calculation results	SUS score
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10		
R1	5	5	5	3	2	2	5	5	3	2	23	57,5
R2	4	4	3	4	4	4	5	5	4	3	20	50
R3	2	3	4	3	3	3	4	4	3	4	19	47,5
R4	5	2	3	1	4	2	4	1	4	1	33	82,5
R5	4	1	3	2	4	4	3	3	2	3	23	57,5
R6	3	1	4	3	5	2	5	4	4	2	29	72,5
R7	2	3	2	1	2	3	4	4	3	4	18	45
R8	4	3	1	3	1	3	3	3	3	3	17	42,5
R9	1	2	3	2	3	2	4	2	2	2	23	57,5
R10	4	1	4	2	3	2	4	4	4	3	27	67,5
R11	3	2	5	2	3	4	2	4	3	4	20	50
R12	5	1	4	2	5	3	4	2	3	1	32	80
R13	2	4	1	4	1	4	4	2	4	2	16	40
R14	5	5	2	5	4	2	2	5	5	5	16	40
R15	1	1	3	4	2	4	5	2	4	2	22	55
R16	5	5	4	5	4	5	4	4	5	4	19	47,5
R17	2	3	4	3	4	2	4	1	3	1	27	67,5
R18	4	2	4	1	3	2	2	4	1	2	23	57,5
R19	2	5	5	5	5	5	5	5	5	5	17	42,5
R20	5	2	4	5	4	2	4	2	5	2	29	72,5
Average score											55,13	

In the table 12, the application evaluation calculation using the SUS method obtained an

average final score of 55.13. Next, an assessment will be made of the score that has been obtained. The SUS method has 3 measurement aspects, namely Acceptability Ranges, Grade Scale, and Adjective Twigs. The following measurement results can be seen in Figure 2.

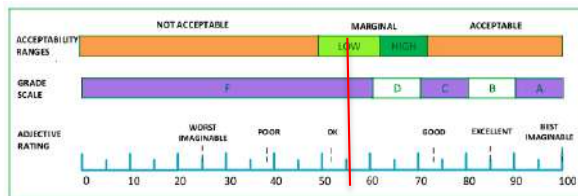


Figure 2. SUS Measurement Results

Based on these 3 aspects, the final average score of SUS in the Acceptability Ranges is at the marginal low for the Grade Scale which is on scale D and finally, the Adjective Rank position is at the OK level. So the results that have been obtained based on this score are that the system is already well used but still requires further improvement in terms of usability.

C. Application Improvement Recommendations

Based on the problem findings obtained after the evaluation, recommendations for problems (H5) and (H6) that have high priority levels of improvement are as follows:

1. Text commands are improved again using a simpler language that is easily understood by ordinary users.
2. There need to be navigation instructions on each page to help users.
3. It is necessary to have an attendance report menu to help users find information about their attendance data recap.
4. Buttons or other action options should have their layout changed so they can be seen and easily found by application users.

CONCLUSION

The results of this research indicate that the aspects requiring high-priority improvement are Error Prevention (H5) and Recognition Rather Than Recall (H6) because they have severity ratings of 3 on the scale. As for the average final severity ratings score obtained from the total of 10 heuristic aspects, it is **1,72** which is then rounded to a scale of **2**.

The results from the SUS testing yielded an average final SUS score of **55,13**. The calculations from the SUS method show that the Acceptability Ranges fall into the **marginal low** status, the Grade Scale is at **level D**, and the Adjective Rating is positioned at the **OK level**.

From the results of research that has been done on PRICILIA Application Usability Analysis at PT. BGR Logistik Indonesia, a conclusion can be drawn, namely that the PRICILIA application is currently not fully easy for users to use to make attendance and obtain information related to presence data. Therefore, 30 recommendations for improvement were made in this study for future application development.

Based on the conclusions from the research results above, several suggestions can be given. Among them, it is hoped that companies can develop the PRICILIA application by considering the recommendations for improvement from this study to increase the usability value of the PRICILIA application.

In the system, it is necessary to redevelop the PRICILIA application interface as well as system functions and existing features to be more effective, efficient, and informative to help users get information related to presence data more easily, as well as improve the development of the application so that it can be used on iOS devices.

And for further research, it is hoped that it will be able to continue with recommendations for improvements in the form of prototypes by paying attention to design atoms in accordance with heuristic principles, as well as re-testing using other methods such as the Think-Aloud Evaluation (TA) method and Cognitive Walkthrough (CW).

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PRE-ECLAMPSIA DIAGNOSIS EXPERT SYSTEM USING FUZZY INFERENCE SYSTEM MAMDANI

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Abstract—Various institutions utilize computer information systems to analyze and process data. An expert system is an information system that is used to help analyze and determine decisions on a problem based on rules determined by experts. This research focuses on creating a prototype expert system for diagnosing pre-eclampsia or pregnancy poisoning in pregnant women based on measuring blood pressure and checking proteinuria. The existing data is then analyzed using the Mamdani system's fuzzy inference method. Supporting theory regarding the fuzzy inference system of Mamdani, pre-eclampsia and its examination indicators will be used as a basis for creating this expert system prototype. The data used were secondary data on preeclampsia patients in the form of medical records of blood pressure measurements, proteinuria examinations and doctor diagnoses of preeclampsia patients at two Regional General Hospitals (RSUD), namely Atambua and Kefamenanu, totaling 20 samples. The interface or user interface of this prototype system is made as simple as possible so that it can be operated by all ordinary people. The programming language used is Visual Basic (VB) with the Visual Studio 2010 developer application. The initial prototype of this system will continue to be developed until it can become a Information systems or real applications used in hospitals. The results of this research are that the expert system for diagnosing preeclampsia can be used well and easily by hospital staff and show congruence between the system diagnosis results and the diagnosis results from obstetricians or experts in the 20 processed data.

Keywords: diagnosis, expert system, fuzzy inference mamdani system, preeclampsia.

Intisari—Berbagai institusi memanfaatkan sistem informasi komputer untuk menganalisa dan mengolah data. Sistem pakar adalah salah satu sistem informasi yang digunakan untuk membantu menganalisa dan menentukan keputusan suatu masalah berdasarkan aturan yang ditentukan oleh pakar. Penelitian ini fokus pada pembuatan *prototype* sistem pakar diagnosa pre-eklampsia atau keracunan kehamilan pada ibu hamil berdasarkan pengukuran tekanan darah dan pengecekan proteinuria, data yang ada selanjutnya dianalisis menggunakan metode *fuzzy inference system* mamdani. Teori pendukung mengenai *fuzzy inference system* mamdani, pre-eklampsia dan indikator pemeriksaannya akan digunakan menjadi dasar dalam pembuatan *prototype* sistem pakar ini. Data yang digunakan adalah data sekunder pasien preeklampsia berupa rekam medis pengukuran tekanan darah, pemeriksaan proteinuria dan diagnosa dokter pasien pre-eklampsia di dua Rumah Sakit Umum Daerah (RSUD) yaitu Atambua dan Kefamenanu sebanyak 20 sampel. Tampilan antarmuka atau *user interface* dari *prototype* sistem ini dibuat sesederhana mungkin agar dapat dioperasikan oleh semua orang awam. Bahasa pemrograman yang digunakan adalah visual basic (VB) dengan aplikasi pengembang visual studio 2010. *Prototype* awal dari sistem ini akan terus dikembangkan sehingga dapat menjadi sistem informasi atau aplikasi yang *real* digunakan pada rumah sakit. Hasil dari penelitian ini adalah sistem pakar diagnosis preeklampsia dapat digunakan dengan baik dan mudah oleh petugas rumah sakit dan menunjukkan kesesuaian antara hasil diagnosa sistem dengan hasil diagnosa dari dokter kandungan atau pakar di 20 data yang diproses.

Kata Kunci: diagnosa, sistem pakar, fuzzy inference system mamdani, pre-eklampsia.

INTRODUCTION

Maternal mortality and perinatal mortality rates in Indonesia are still very high. According to the results of the Inter-Census Population Survey (SUPAS) conducted by the Central Bureau of Statistics (BPS) in 2015, the maternal mortality rate was 305 per 100,000 live births. When compared to the target that the government wants to achieve in 2010 of 125/100,000 live births, this figure is still relatively high. Maternal mortality in East Nusa Tenggara in 2017 was 163 per 100,000 live births (Bardja, 2020), the Maternal Mortality Rate (MMR) in North Timor- Tengah District in 2014 was 137 people. The direct causes of death include pre-eclampsia or eclampsia by 5%, bleeding by 50%, infection by 17%, other causes by 28%.

The impact that can be caused by preeclampsia on the mother is premature birth, oliguria, death, while the impact on the baby is stunted fetal growth, oligohydramnios, can also increase morbidity and mortality (Nassa, 2018). Pre-eclampsia with seizures, or what is known as eclampsia, which is not properly controlled can lead to permanent disability or even cause death of mother and baby. If eclampsia is not treated quickly there will be loss of consciousness and death due to heart failure, kidney failure, liver failure or brain hemorrhage. Therefore the occurrence of seizures in patients with eclampsia must be avoided. Risk factors for pre-eclampsia are maternal age (less than 16 years or more than 45 years), primigravida, presence of hypertension before pregnancy, multiple pregnancies, molar pregnancies, obesity, history of pre-eclampsia in previous pregnancies (Hanif et al., 2022). By knowing the risk factors, early detection of pre-eclampsia in pregnant women needs to be done so that later it can be treated more quickly as a prevention of further complications.

Several tests will be carried out to detect whether a pregnant woman has preeclampsia, namely blood pressure, urinalysis, several other optional screening tests to measure protein levels (PAPP-A) and to measure fetal alpha-fetoprotein (AFP) levels, as well as monitor development baby (Handayani, 2022). This examination is always carried out in hospitals, health centers or other health clinics. With a practical application that can be applied efficiently and effectively for the early diagnosis of pre-eclampsia, ordinary people can make an early diagnosis and can immediately start treatment (Anindita, et al., 2023).

There are several decision-making systems used in diagnosing a disease, one of which is a fuzzy decision-making system or often called the Fuzzy Inference System (FIS). There are 3 FIS methods

that can be used in processing decisions, namely the Tsukamoto method, the Mamdani method and the Sugeno method (Surorejo, Chaeriko, & Ananda, 2022)

There are many researchers who have applied FIS in the process of diagnosing diseases, including diagnosing fever in toddlers, diagnosing coronary heart disease, diagnosing diabetes mellitus, diagnosis of ear, nose and eye disease or ENT, detection of lymph node disease, diagnosis of eye disease and risk diagnosis of heart disease. However, detecting pre-eclampsia in pregnant women has never been done (Juwita, Sarjon, & Yuhandri, 2021), (Sitinjak, 2021), (Rizki & Maulana, 2018), (Rizky & Hakim, 2020), (Novianti, Pribadi, & Saputra, 2018), (Dona, Maradona, & Masdewi, 2021), (Anindita et al., 2023), (Ananta, Putra, Purnawan, Purnami, & Putri, 2018), and (Hanif et al., 2022). (Nizar, Shafira, Aufaresa, Awliya, & Athiyah, 2021), diagnosed diabetes using the three FIS methods and obtained the result that the Sugeno method had the highest level of accuracy in analyzing, namely 97.33%, followed by the Mamdani method of 95.33% and the Tsukamoto method had the highest accuracy. smaller than the Mamdani method, for errors in analyzing, the Sugeno method is only 2.67%, the Mamdani method is 4.67% and the Tsukamoto method is 5.78%, for manual calculation time, the Tsukamoto method is the method that requires the least time compared to the Mamdani and Sugeno methods while for calculations, the Mamdani method is the most complicated method.

An expert system is an information system that contains the knowledge of an expert so that it can be used for consultation. An expert's knowledge possessed by this Expert System is used as a basis for answering questions (Supriyono & Fadila, 2022). Expert systems have the ability to recommend a series of actions or user behavior to be able to carry out a correct and accurate correction system. Where, this system also utilizes the capabilities of the reasoning process to be able to reach conclusions based on existing data and facts (Simarmata, 2021)

The use of expert systems in the medical world has been widely used (Dona et al., 2021), but so far expert systems have not been applied to diagnose preeclampsia in pregnant women. Based on the indicators previously explained, the expert system that will be created uses blood pressure and the amount of proteinuria to calculate the level of preeclampsia by implementing fuzzy calculations and rules. In processing data using FIS, the help of Matlab software can be used. However, this software only contains the Mamdani method, while the Sugeno method and the Tsukamoto method are not available (Athiyah et al., 2021).

Furthermore, with the help of Visual Basic development software, a GUI (Graphical User Interface) based prototype of FIS was created so that later the system could be more easily used by medical staff or lay people (Rizky & Hakim, 2020).

This research aims to build a prototype information system for decision making for preeclampsia diagnosis in pregnant women based on blood pressure and proteinuria. After system design, the next process is implementing the Mamdani Fuzzy Inference System method in the form of the Visual Basic programming language, and then it will be compared with the diagnosis made by the doctor to check how accurate the system that has been built is.

MATERIALS AND METHODS

This research is a literature study and applied research. A literature study was conducted to find theories about Mamdani's FIS and pre-eclampsia and its examination indicators which would later become the basis for making a diagnostic system. After the system design process, pre-eclampsia case data will be collected from two Regional General Hospitals (RSUD), namely Atambua Hospital and Kefamenanu Hospital.

The data taken is secondary data in the form of medical record data measuring blood pressure, checking proteinuria and doctor's diagnosis of pre-eclampsia patients from 2021 to 2022. The data used is 20 samples, the existing data has received permission from the patient but there are some who do not want their data to be used, so the data used is only limited to the number above. The data is then processed using the Mamdani FIS method with the following steps.

I. Methods Stages

a. Fuzzification

The process of converting input variables with firm values (crisp) into linguistic variables (fuzzy) uses the membership functions that have been developed. There are 3 membership function curves that will be used in this study, namely:

Membership function of descending linear representation (parameters (a,b)):

$$\mu(x) = \begin{cases} 1; & x \leq a \\ \frac{b-x}{b-a}; & a \leq x \leq b \\ 0; & x \geq b \end{cases} \dots\dots\dots (1)$$

For more details, the geometric shape of this function can be seen in Figure 1.

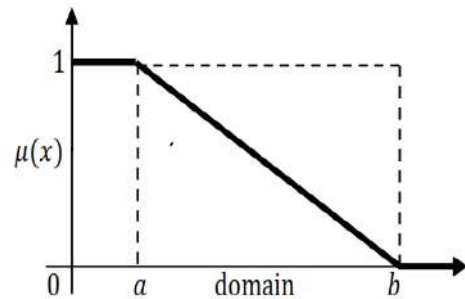


Figure 1. Graph of Descending Linear Functions

Ascending linear representation membership function (parameters (a,b)):

$$\mu(x) = \begin{cases} 0; & x \leq a \\ \frac{x-a}{b-a}; & a \leq x \leq b \\ 1; & x \geq b \end{cases} \dots\dots\dots (2)$$

For more details, the geometric shape of this function can be seen in Figure 2.

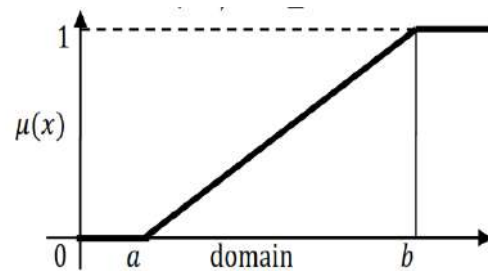


Figure 2. Graph of Increasing Linear Functions

Membership function (parameters (a,b,c)) :

$$\mu(x) = \begin{cases} 0; & x \leq a \text{ or } x \geq c \\ \frac{x-a}{b-a}; & a \leq x \leq b \\ \frac{c-x}{c-b}; & b \leq x \leq c \\ 1; & x = b \end{cases} \dots\dots\dots (3)$$

For more details, the geometric shape of this function can be seen in Figure 3.

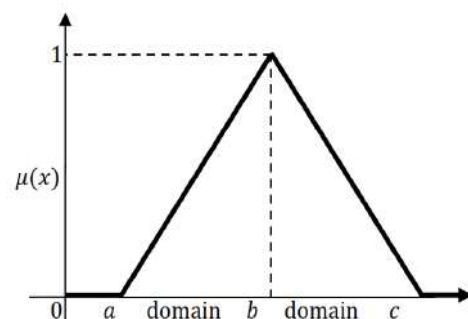


Figure 3. Graph of Triangle Linear Functions

b. Inference

The stage of changing the fuzzy input into fuzzy output by following the IF-AND-THEN rules. Furthermore, at this stage calculations are also carried out for fuzzy decision making. The Mamdani FIS method is often referred to as the Min-Max method because the process of determining the final decision uses the Min operation and the Max operation. The Min operation is performed to determine the membership value as a result of the operation of two or more sets, often referred to as fire strength or α -predicate by using the AND operator with the following equation

$$\alpha - \text{predikat}_i = \min(\mu_A(x), \mu_B(x)) \dots \dots \dots (4)$$

where i represents the ith rule from a combination of rules formed from any data.

Next, the Max operation is carried out, namely the operation to determine the combination of all existing α -predicates. This operation is carried out using the OR operator with the following equation:

$$\mu(x) = [R_1] \cup [R_2] \cup \dots \cup [R_n] \dots \dots \dots (5)$$

$$= \max\{\alpha - \text{predikat}_1, \dots, \alpha - \text{predikat}_n\}$$

with $[R_i], i=1,2,\dots,n$ stating the number of rules formed from any data.

c. Defuzzification

The process of changing the output with fuzzy values obtained from inference into input with firm values (crisp) using a membership function. The FIS Mamdani method defuzzification process in this research uses the Centroid method with the following formula:

$$Z_0 = \frac{\int_a^b z \cdot \mu(z) dz}{\int_a^b \mu(z) dz} \dots \dots \dots (6)$$

After the system design process is complete, the next step is to compare the diagnosis results based on the processing with the diagnosis system that has been created and the diagnosis based on the experts (doctors) decision to validate how accurate the diagnosis system that has been created.

II. Data Analysis

Determination of the decision to diagnose pre-eclampsia is based on 2 factors, namely blood pressure and proteinuria. These two variables then become input variables for the Mamdani FIS diagnostic system.

a. Blood Pressure Input Variable

The fuzzy set for the input variable blood pressure is divided into 4 sets, namely low blood

pressure, normal blood pressure, grade I hypertension and grade II hypertension. The domains of the 4 fuzzy sets can be seen in the membership function graph presented in Figure 4.

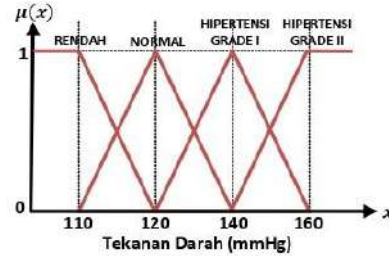


Figure 4. Graph of Blood Pressure Membership Function Graph

Meanwhile, the membership function of the blood pressure variable based on the graph is as follows:

$$\mu_{TD-RENDAH}(x) = \begin{cases} 1; & x \leq 110 \\ \frac{120-x}{10}; & 110 \leq x \leq 120 \\ 0; & x \geq 120 \end{cases}$$

$$\mu_{TD-NORMAL}(x) = \begin{cases} 0; & x \leq 110 \text{ or } x \geq 140 \\ \frac{x-110}{10}; & 110 \leq x \leq 120 \\ \frac{140-x}{20}; & 120 \leq x \leq 140 \\ 1; & x = 120 \end{cases}$$

$$\mu_{HG-I}(x) = \begin{cases} 0; & x \leq 120 \text{ or } x \geq 160 \\ \frac{x-120}{20}; & 120 \leq x \leq 140 \\ \frac{160-x}{20}; & 140 \leq x \leq 160 \\ 1; & x = 140 \end{cases}$$

$$\mu_{HG-II}(x) = \begin{cases} 0; & x \leq 140 \\ \frac{x-140}{10}; & 140 \leq x \leq 160 \\ 1; & x \geq 160 \end{cases}$$

with TD = Blood Pressure and HG = Grade Hypertension.

b. Proteinuria Input Variable

There are 5 categories to describe the amount of protein in urine (proteinuria). These five indicators are determined based on the protein precipitate test by heating urine until it boils (boiling test). This examination is carried out by inserting 10-15 mL of urine into a tube and heating the top of the tube until it boils and then observing changes in the urine sample in the tube. Interpretations of the five indicators are presented in Table 1.

Table 1. Proteinuria Examination Conditions and Categories

No.	Categories	Conditions
1.	Negatif (-)	No fog
2.	Positif 1 (+1)	Light fog
3.	Positif 2 (+2)	Clear fog
4.	Positif 3 (+3)	White turbidity
5.	Positif 4 (+4)	There are white lumps

From here, a fuzzy set and its domain are then formed as presented by the membership function graph in Figure 5.

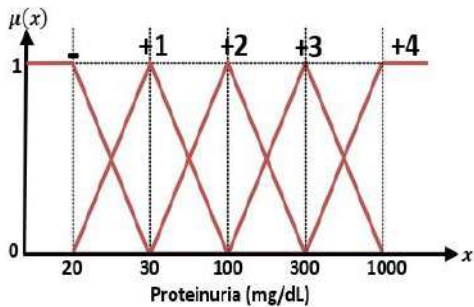


Figure 5. Proteinuria Membership Function Graph

Meanwhile, the function for collecting proteinuria variables based on graphs is in the following equation:

$$\mu_{p-}(x) = \begin{cases} 1; & x \leq 20 \\ \frac{30-x}{10}; & 20 \leq x \leq 30 \\ 0; & x \geq 30 \end{cases}$$

$$\mu_{p+1}(x) = \begin{cases} 0; & x \leq 20 \text{ or } x \geq 100 \\ \frac{x-20}{10}; & 20 \leq x \leq 30 \\ \frac{100-x}{70}; & 30 \leq x \leq 100 \\ 1; & x = 30 \end{cases}$$

$$\mu_{p+2}(x) = \begin{cases} 0; & x \leq 30 \text{ or } x \geq 300 \\ \frac{x-30}{70}; & 30 \leq x \leq 100 \\ \frac{300-x}{200}; & 100 \leq x \leq 300 \\ 1; & x = 100 \end{cases}$$

With p-1 = negative proteinuria, p+1 = positive proteinuria 1, and so on.

c. Proteinuria Output Variable

There are 4 fuzzy sets for this output variable, namely non-pre-eclampsia, pre-eclampsia, severe pre-eclampsia type I and severe pre-eclampsia type II. The domain for each fuzzy set can be seen in the membership function graph

for pre-eclampsia status which is presented in Figure 6.

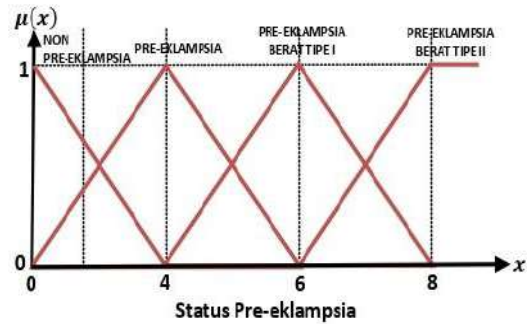


Figure 6. Graph of Membership Function Status of Pre-eclampsia

Meanwhile, the membership function of the pre-eclampsia status variable based on the graph is in the following equation:

$$\mu_{NON-PRE}(x) = \begin{cases} 1; & x \leq 0 \\ \frac{4-x}{4}; & 0 \leq x \leq 4 \\ 0; & x \geq 4 \end{cases}$$

$$\mu_{PRE}(x) = \begin{cases} 0; & x \leq 0 \text{ or } x \geq 8 \\ \frac{x}{4}; & 0 \leq x \leq 4 \\ \frac{6-x}{2}; & 4 \leq x \leq 6 \\ 1; & x = 4 \end{cases}$$

$$\mu_{PRE-BERAT-I}(x) = \begin{cases} 0; & x \leq 4 \text{ or } x \geq 8 \\ \frac{x-4}{2}; & 4 \leq x \leq 6 \\ \frac{8-x}{2}; & 6 \leq x \leq 8 \\ 1; & x = 6 \end{cases}$$

$$\mu_{PRE-BERAT-II}(x) = \begin{cases} 0; & x \leq 6 \\ \frac{x-6}{4}; & 6 \leq x \leq 8 \\ 1; & x \geq 8 \end{cases}$$

With NON-PRE = Negative Pre-eclampsia, PRE = Pre-eclampsia, PRE-SEVERE-I = Severe Pre-eclampsia Type I, PRE-SEVERE-II = Severe Pre-eclampsia Type II.

d. Fuzzy Rule Formulation

The fuzzy rule creation stage uses IF ... AND ... THEN logic. Based on the opinions of experts (doctors and nurses), 27 rules were formed as follows.

Table 2. Fuzzy Rule

RULE	IF	BLOOD PRESSURE	AND	PROTEINURIA	THEN	PREECLAMPSIA STATUS
[R1]	IF	LOW	AND	-	THEN	NON PREECLAMPSIA
[R2]	IF	LOW	AND	+1	THEN	NON PREECLAMPSIA
[R3]	IF	LOW	AND	+2	THEN	NON PREECLAMPSIA
[R4]	IF	LOW	AND	+3	THEN	NON PREECLAMPSIA
[R5]	IF	LOW	AND	+4	THEN	NON PREECLAMPSIA
[R6]	IF	NORMAL	AND	-	THEN	NON PREECLAMPSIA
[R7]	IF	NORMAL	AND	+1	THEN	NON PREECLAMPSIA
[R8]	IF	NORMAL	AND	+2	THEN	SEVERE PREECLAMPSIA I
[R9]	IF	NORMAL	AND	+3	THEN	SEVERE PREECLAMPSIA I
[R10]	IF	NORMAL	AND	+4	THEN	SEVERE PREECLAMPSIA I
[R11]	IF	NORMAL	AND	-	THEN	PREECLAMPSIA
[R12]	IF	NORMAL	AND	+1	THEN	PREECLAMPSIA
[R13]	IF	HYPERTENSION GRADE I	AND	-	THEN	PREECLAMPSIA
[R14]	IF	HYPERTENSION GRADE I	AND	+1	THEN	PREECLAMPSIA
[R15]	IF	HYPERTENSION GRADE I	AND	+2	THEN	SEVERE PREECLAMPSIA I
[R16]	IF	HYPERTENSION GRADE I	AND	+3	THEN	SEVERE PREECLAMPSIA I
[R17]	IF	HYPERTENSION GRADE I	AND	+4	THEN	SEVERE PREECLAMPSIA I
[R18]	IF	HYPERTENSION GRADE II	AND	-	THEN	SEVERE PREECLAMPSIA II
[R19]	IF	HYPERTENSION GRADE II	AND	-	THEN	PREECLAMPSIA
[R20]	IF	HYPERTENSION GRADE II	AND	+1	THEN	PREECLAMPSIA
[R21]	IF	HYPERTENSION GRADE II	AND	+1	THEN	SEVERE PREECLAMPSIA II
[R22]	IF	HYPERTENSION GRADE II	AND	+2	THEN	SEVERE PREECLAMPSIA I
[R23]	IF	HYPERTENSION GRADE II	AND	+2	THEN	SEVERE PREECLAMPSIA II
[R24]	IF	HYPERTENSION GRADE II	AND	+3	THEN	SEVERE PREECLAMPSIA I
[R25]	IF	HYPERTENSION GRADE II	AND	+3	THEN	SEVERE PREECLAMPSIA II
[R26]	IF	HYPERTENSION GRADE II	AND	+4	THEN	SEVERE PREECLAMPSIA I
[R27]	IF	HYPERTENSION GRADE II	AND	+4	THEN	SEVERE PREECLAMPSIA II

III. System Design

The system design process uses a structured approach where structured design is the activity of transforming the analysis results into a plan to be implemented. A structured approach is equipped with the tools and techniques needed in system development, so that the final result of the developed system will be a system with a well-defined and clear structure. The reasons for using a structured design are that it is relatively simple, easy to understand, commonly known in various industries, and allows for validation between various requirements. The system design in this research uses context diagrams, data flow diagrams, and system usage flowcharts.

a. Context Diagram

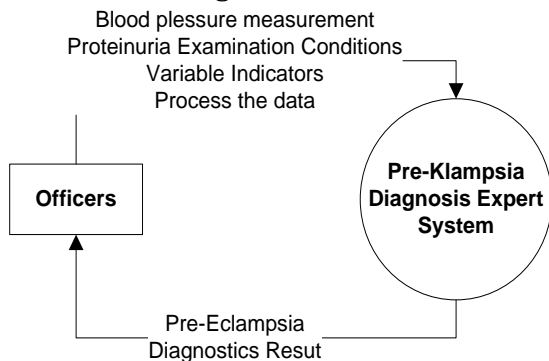


Figure 7. Context Diagram System

The only one user of the system is a medical officer. The officers interacts with the system by providing data in the form of measuring blood pressure and the amount of proteinuria using a keyboard, then the system will process the data and display it on the monitor screen. The results of the system diagnosis will be given to the doctor for further analysis.

b. Data Flow Diagram

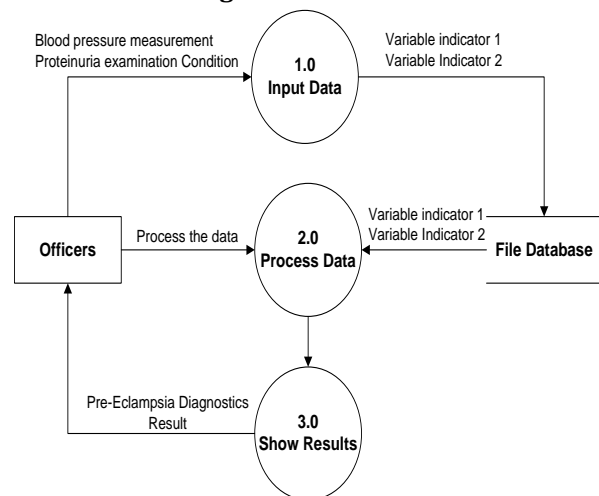


Figure 8. Data Flow Diagram System

Data flow diagrams (DFD) describe the relationships between system, user entities,

processes in the system, and databases in system. User enters blood pressure data and the amount of proteinuria through the 1.0 process and then saves it in a database file as variable indicator 1 and variable indicator 2. Data that has been stored is used in process 2.0 and forwarded to process 3.0 to display the results back to the officer.

c. System Usage Flowchart

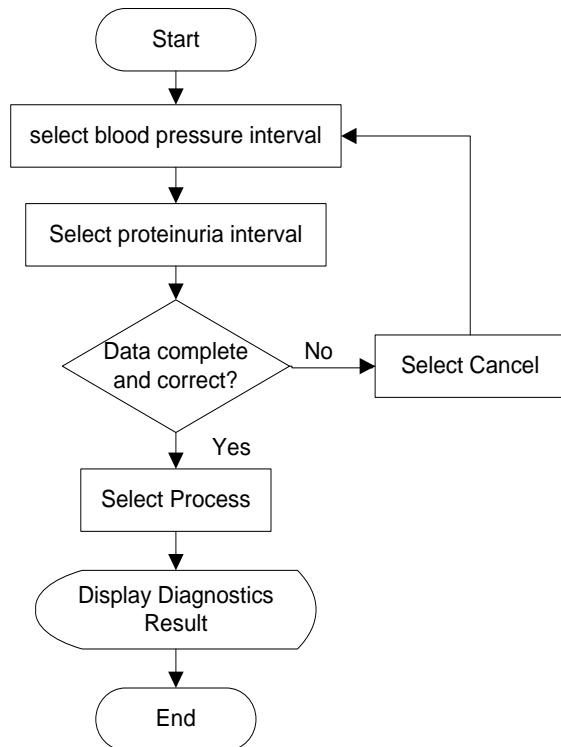


Figure 9. Flowchart Usage System

User runs the program, starts by selecting the blood pressure value interval, then selecting the proteinuria value interval, if the data correct then the user choose the process, else user can cancel the data. After the diagnostic, process results are displayed on the monitor screen

d. User Interface Design

PRE-EKLAMPسيا FUZZY INFERENCE SYSTEM DIAGNOSTIC

Blood Pressure (mmHg) v

Proteinuria (mg/dL) v

Diagnostic Result

Process Cancel Exit

Figure 10. User Interface Design System

The user interface is made as simple as possible to make it easier for users to access the system. There are several components such as labels, combo-box, text-box, and buttons. Data is filled in the combo-box and the command is given by clicking on the button.

RESULTS AND DISCUSSION

Presentation of results using case studies:

It is known that patient a.n. Mrs. V.D.B has a blood pressure of 140/90 mmHg and proteinuria +1. By using the FIS diagnostics that have been developed, the diagnosis status is pre-eclampsia. System demo results are shown in Figure 11.

Fuzzy Mamdani Inference System

PRE-EKLAMPسيا DIAGNOSTIC SYSTEM

BLOOD PRESSURE (mmHg) 131-150 v Hipertensi 1

PROTEINURIA (mg/dL) 41-65 v Positif 1(+1)

DIAGNOSTIC RESULT Pre Eklampsia

PROCESS CANCEL EXIT

Figure 11. System running results

After the process of implementing the method and making the system prototype is complete, the next step is validation. validation process to compare the suitability between diagnosis results based on expert decisions and FIS calculations. A system is valid when there are more appropriate comparisons than inappropriate ones. The following is a comparison of the results of diagnoses based on experts and systems from data on 20 patients from Atambua Hospital and Kefamenanu Hospital. The comparison is presented in Table 3.

In the medical world, only severe pre-eclampsia is known and there is no division between type I and type II severe pre-eclampsia. This was only created for the purpose of combining rules at the inferencing stage (rule base), so even though in the system diagnosis decision PEB I and PEB II are written, there is no difference between the two, either in follow-up examination or treatment.

Table 3. Comparison of Diagnostic Results between Experts and Systems

No.	Patient	Examination		Diagnosis Result		Validation (Appropriate and inappropriate)
		Blood Pressure (mmHg)	Proteinuria	Expert	System	
1	V. D. B.	140/90	+1	PE	PE	Appropriate
2	R. R.	162/80	-	PEB II	PEB II	Appropriate
3	Yosefina A. N.	155/111	+3	PEB I	PEB I	Appropriate
4	Maria Balok	183/110	+1	PEB II	PEB II	Appropriate
5	Emerencia Merin	150/100	+2	PEB I	PEB I	Appropriate
6	Atriana F. Fahik	156/94	+2	PEB I	PEB I	Appropriate
7	Yustina Abu Leto	141/95	+2	PEB I	PEB I	Appropriate
8	Ermelinda L	200/120	+3	PEB II	PEB II	Appropriate
9	Kristina T	143/83	+3	PEB I	PEB I	Appropriate
10	Marsela W. L.	140/90	+2	PEB I	PEB I	Appropriate
11	Maria T.	156/107	+1	PE	PE	Appropriate
12	Kristina S.	200/140	+2	PEB II	PEB II	Appropriate
13	Oktaviana L. F.	110/70	+2	NPE	NPE	Appropriate
14	Lorensia H.	149/95	+2	PEB I	PEB I	Appropriate
15	Maria A. S.	107/74	-	NPE	NPE	Appropriate
16	Victoria M. A. T.	156/104	+2	PEB I	PEB I	Appropriate
17	Graciana N. Mau	150/100	+2	PEB I	PEB I	Appropriate
18	Ines Da Silva G.	148/106	+2	PEB I	PEB I	Appropriate
19	Maria Hati	165/97	+3	PEB II	PEB II	Appropriate
20	Maria J. Asa	156/95	+2	PEB I	PEB I	Appropriate

Note: NPE = Non-Preeclampsia, PE = Preeclampsia, PEB I = Severe Pre-eclampsia Type I, PEB II = Severe Pre-eclampsia Type II

Patient data serial number 2 with the initials R.R. has two possible diagnoses, namely PEB or NPE. Patients with this condition will be diagnosed with PEB if apart from the results of this screening, there are other symptoms such as headache, vomiting or blurred vision. If the patient does not have the symptoms in question then the patient is diagnosed as NPE. Meanwhile, patient data for serial numbers 13 and 15 are examples of cases that are not preeclampsia cases.

Based on Table 3, a comparison of the 20 data shows that the results are an Appropriate between the expert's decision and the decision of the diagnosis system with FIS Mamdani, meaning that the diagnosis system can be used to help the medical team or the lay public in detecting preeclampsia as early as possible so that it can prevent pre-eclampsia severe disease and eclampsia which can cause death.

CONCLUSIONS

Based on the results and discussion, there are several conclusions, including: the Mamdani Fuzzy Inference System method with blood pressure indicators and the amount of proteinuria content can be used to process data in a preeclampsia diagnosis system in pregnant women. The system's decision results are in accordance with the diagnosis delivered by the expert (doctor), with the level of accuracy of this system reaching 95.62% and therefore this expert system can be trusted to predict preeclampsia early so that the death of pregnant women due to

preeclampsia or eclampsia can be achieved. avoided. This expert system, designed with a Graphical User Interface (GUI) approach, has a simple appearance, this makes it easier for users (officers) to understand the process and how to use the system.

For further research, additional data needs to be added so that the system testing parameters can be more accurate. The 20 data used in this study still cannot represent the characteristics of all patients suffering from preeclampsia. It requires a large amount of data to become an accurate parameter. In addition, the system can be developed by considering other factors such as a history of preeclampsia in previous pregnancies, maternal age (less than 16 years or more than 45 years), primigravida, multiple pregnancies, molar pregnancies, and obesity.

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CLASSIFICATION OF POTATO LEAF DISEASES USING CONVOLUTIONAL NEURAL NETWORK

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Abstract—Potatoes are an agricultural product that has the fourth highest content of wheat flour after corn, wheat, and rice. Although potatoes play a critical role in agriculture, this crop is susceptible to various diseases and pests. There are several potato leaf diseases that are not yet known to farmers. Dry spot potato leaf disease (late blight) and late blight. If not treated, this disease on potato leaves will spread to the stem and reduce crop yields, causing crop failure. By using technology in the form of digital image processing, this problem can be overcome. This research proposes an appropriate method for detecting disease in potato leaves. Classification will be carried out in three classes, namely, Early Blight, Healthy and Late Blight using the Deep Learning method of Convolutional Neural Network (CNN). The data used comes from an online dataset via the kaggle.com page with the file name Potato Disease Leaf Dataset (PLD) totaling 3251 training datasets which are then divided into training, testing, and validation. The processes carried out are image pre-processing, image augmentation, then image processing using a Convolutional Neural Network (CNN). In the classification process using the CNN method with RMSprop optimizer, the accuracy was 97.53% with a loss value of 0.1096.

Keywords: Classification, CNN, Potato Leaf, RMSprop.

Intisari—Kentang merupakan produk pertanian yang mempunyai kandungan tepung terigu tertinggi keempat setelah jagung, gandum dan beras. Meskipun kentang memiliki peranan yang sangat penting dalam pertanian, tanaman ini rentan terhadap berbagai penyakit dan hama. Ada beberapa penyakit daun kentang yang belum diketahui petani. Penyakit daun kentang bercak kering (penyakit busuk daun) dan penyakit busuk daun. Jika tidak diobati, penyakit pada daun kentang ini akan menyebar hingga ke batang dan

menurunkan hasil panen dapat menyebabkan gagal panen. Dengan menggunakan teknologi berupa pengolahan citra digital hal tersebut dapat diatasi, penelitian ini mengusulkan metode yang tepat untuk mendeteksi penyakit pada daun kentang. Klasifikasi akan dilakukan dengan tiga kelas yaitu *Early Blight*, *Healthy*, dan *Late Blight* dengan menggunakan metode *Deep Learning Convolutional Neural Network* (CNN). Data yang digunakan bersumber dari dataset *online* melalui laman [kaggle.com](https://www.kaggle.com) dengan nama file *Potato Disease Leaf Dataset* (PLD) sebanyak 3251 dataset pelatihan yang kemudian dibagi menjadi pelatihan, pengujian dan validasi. Proses yang dilakukan adalah pra-pemrosesan gambar, augmentasi gambar, kemudian pemrosesan gambar menggunakan *Convolutional Neural Network* (CNN). Pada proses klasifikasi menggunakan metode CNN dengan *RMSprop optimizer* diperoleh akurasi sebesar 97,53% dengan nilai loss sebesar 0,1096.

Kata Kunci: Klasifikasi, CNN, Daun Kentang, RMSprop.

INTRODUCTION

One of the food plants that grow most widely in the Indonesian highlands and contains fiber and vitamin C, which is good for body health, is potatoes (Amatullah, et al., 2021). Potatoes are an agricultural product that has the fourth highest content of wheat flour after corn, wheat, and rice (Lesmana, et al., 2022). Potatoes are also a significant export commodity in many countries, contributing to the global agricultural economy (Erlangga, 2023).

Although potatoes are critical to global food security, this crop is also susceptible to various diseases and pests. One of the main problems faced in potato cultivation is potato leaf disease. The variety of diseases that can occur in potatoes

certainly makes it difficult for farmers to identify diseases that attack potato plants (Teresia Ompusunggu, 2022). Potato leaf disease dry spot also called early blight. Cold and damp places are one of the factors for developing leaf blight (Fitriana and Hakim, 2019) Late blight disease will appear during the plant's growth period between the 5th and 6th weeks. The initial symptom of this late blight disease is the presence of wet spots on the edges of the leaves which can also be in the middle. Then these spots will widen and the color of the leaves will change to brown or gray. Meanwhile, the symptoms of dry spot disease (early blight) are characterized by dry spots in the form of brown circles on the underside of the leaves (Fuadi and Suharso, 2022).

Diseases on potato leaves if left unchecked will spread to the stalks reduce crop yields and cause crop failure (Rozaqi, et al., 2021). This disease can be recognized visually because it has unique color and texture characteristics. But visual recognition has a drawback, namely that it is difficult to recognize the similarities between one type of disease and another (Lubis, et al., 2023). In dealing with the problem of potato leaf disease, this has been done a lot (Ahmad and Iskandar, 2020) not only in the agricultural sector but also in the technological sector, he has also taken part in identifying diseases in potato plants (Rashid, et al., 2021) using image processing or what is usually called digital image processing (Hidayat, et al., 2022).

Several studies that discuss the classification of potato leaf diseases include research on the Identification of Potato Leaf Diseases Based on Texture and Color Features Using the K-Nearest Neighbor Method in research (Amatullah, et al., 2021) carried out the process of resizing, feature extraction, dataset division (training, testing) and calculating accuracy and predictions using K-Nearest neighbor resulting in an accuracy of 80%.

Potato Leaf Disease Classification Using Deep Learning Approach (Sholihati, et al., 2020) using 5,100 data from Google which was divided into 5 classes which were processed using the VGG16 and VGG 19 models to get an accuracy of 91.0% and 90%.

Implementation of Potato Leaf Disease Object Detection Using the Convolutional Neutral Network Method (Nauval and Lestari, 2022) In this research, classification was carried out with three classes, namely healthy leaves, early blight and late blight using a Convolutional Neural Network (CNN) architecture. The results of this research are considered good because the 10th epoch with a batch size of 20 produced training accuracy of 95% and validation accuracy of 94%.

Based on several studies, it shows that CNN has a better level of accuracy on image data. The Convolutional Neural Network method is very popular in deep learning circles because CNN extracts features from input in the form of images and then changes the dimensions of the image to be smaller without changing the characteristics of the image (Omori and Shima, 2020) Therefore, this research implemented the CNN method as a classification of potato leaf diseases. It is hoped that the CNN method will be useful for identifying potato leaf diseases so that it can reduce the number of diseases on potato leaves.

MATERIALS AND METHODS

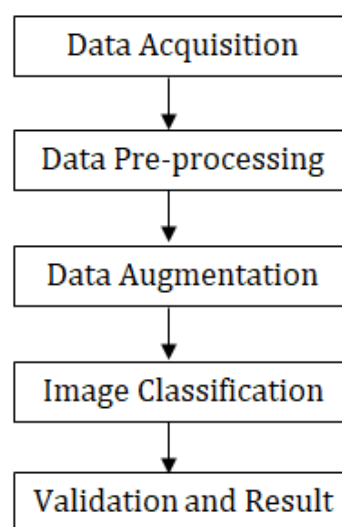


Figure 1. Research Methods

1. Data Acquisition

The first step is to take and collect the images to be studied which are sourced from an online dataset via the www.kaggle.com page with the file name Potato Disease Leaf Dataset (PLD) which was uploaded by Rizwan Saaed in jpg format. with dimensions of 256 x 256 pixels. The images taken from this source were 3251 images with the data details as follows:

Tabel 1. Dataset Acquisition

Data Type	Class	Total Images
Data Training	Early Blight	1303
	Healthy	816
	Late Blight	1132
Total		3251

The image below is a dataset of potato plant leaves which are divided into 3 classes, namely Early Blight, Healthy, and Late Blight. This dataset is then placed in the Google Drive folder.

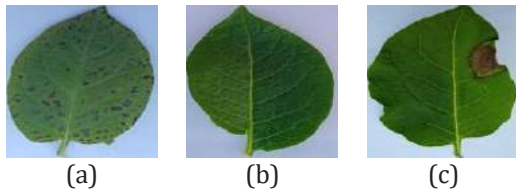


Figure 2. (a) Early Blight, (b) Healthy, (c) Late Blight

2. Pre-Processing Data

In the pre-process, the image resizing stage is carried out. The resizing stage is changing the horizontal (horizontal) resolution and perpendicular (vertical) resolution. The purpose of resizing is so that the data that will later be used can be displayed in the same form or without varying sizes because resizing can result in less memory being used. In this research, the image was resized from its actual size of 256x256 to 200x200.

3. Augmentation Data

Data augmentation needs to be applied in this study because 3251 datasets are still inadequate to get optimal performance. The augmentation parameters used in this study are carried out automatically by applying simple geometric transformations, such as translations, rotation, change in scale, shearing, vertical and horizontal flips.

4. Image Classification Using CNN

One type of neural network commonly used on image data is CNN. Because of the depth of the network level, CNN is included in the Deep Neural Network type and is often used in image data. There are two methods used by CNN, namely classification using feedforward and learning stages using backpropagation.

Around 1988 Yann LeCun introduced CNN. Deep learning has improved and become successful since CNN was introduced and became one of the methods of Deep Learning. Long before that, in the 1950s, Hubel and Wisel conducted research on the visual cortex, which is part of the cat's brain. They found that there is a small part of cells that are sensitive to certain areas of the eye in the visual cortex. There are 2 types of visual cortex discovered by Hubel and Wisel, namely simple cells and complex cells. From the results of his observations, Kunihiro (Darmanto, 2019) designed the Neocognitron which is a Hierarchical Multilayered Neural Network model in the 1980s. This model is then used for several cases such as character classification from handwriting (Handwriting Character Recognition).

There are similarities in the structure that CNN has with artificial neural networks. In image classification, CNN receives input or input images to

be processed and classified into certain categories. The difference between CNN and ANN is in the additional architecture of CNN which is optimized for the features in the input image. There are several main components in CNN, including (Peryanto, et al., 2020):

1. Convolution Layer
2. Pooling Layer
3. Fully Connected Layer
4. Dropout

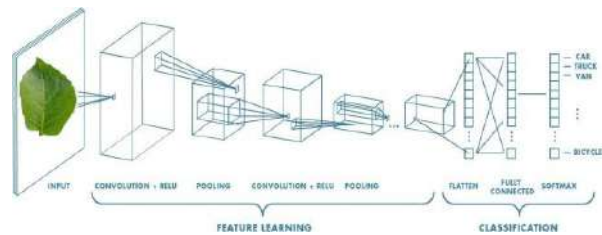


Figure 3. Convolutional Neural Network Architecture

Building Model

Using the CNN algorithm, the sequential model is formed. Keras helps to construct this model section by section, with a Convolution two-dimensional layer for handling images & image input size (256,256) whatever the size image inputted. There was a flat layer among the two-dimensional layer of convolution as well as the dense layer acting as a bridge between them. For this model, ReLU or rectified linear units are used in the form of an enabling function. In the framework, SoftMax was introduced as an activation for forecasting depending on the maximum likelihoods. The equation for the SoftMax function is given below:

$$P(x) = \frac{e^{x^T W^i}}{\sum_{k=1}^k e^{x^T W^i}} \dots \dots \dots (1)$$

Here, W signifies X and W's internal product.

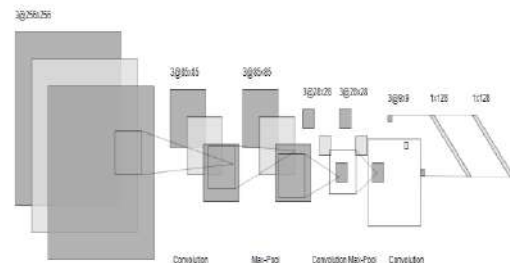


Figure 4. Model of CNN

Compiling the Model

The use of "Adam" and "RMSprop" as an optimizer. This is an effective optimization tool throughout the training period to change the learning rate. For our loss function to make things

easier to realize, categorical cross-entropy is used to train the system and include an accuracy metric to represent the accuracy score on the validation set (Asif, et al., 2020).

RESULTS AND DISCUSSION

To find the best accuracy in the CNN model, several parameter calculations are required. Comparing several optimizers and epochs will be carried out in this research which is a step in the CNN model learning process, where the number of epochs to be determined can influence the size of the learning process and will stop at the time and value determined by iteration. According to previous research, the number of epochs is influenced by several factors, namely the amount of data, learning rate and optimizer. But the more you add, the more often the network weights will be updated. So it can be assumed that the measure of time will be linear with the number of data sets. A difference in numbers that is too small will usually result in accuracy results that are not much different. So the epochs that will be used in this research are 10 and 20 epochs with two optimizers, namely Adam and RMSporp.

This classification process was carried out with 3251 data which was divided into training, testing and validation data, then used 32 batch sizes. The next step is to carry out training on potato leaf images which have been divided into fit models.

1. Comparison of Epoch with Adam Optimizer

Determining the number of epochs usually depends on the research by looking at the number of data samples. The following are the results of comparing epochs with training results using Adam optimizer.

Table 2. Comparison of Epoch with Adam Optimizer

Epoch	Accuracy	Loss
10	0.9506	0.1403
20	0.9432	0.1707

Based on Table 2, the results of the epoch iteration can be seen by using the Adam optimizer which produces different accuracies, namely the accuracy at epoch 10 get 95.06% with a loss value of 0.1403, then epoch 20 get 94.32% accuracy with a loss value of 0.1707 so it can be seen that from the two epochs the accuracy is obtained. best at 10 epochs.

From the results of the confusion matrix shown in table 3, it can be explained that based on table 2, which shows the results of predicting the model on testing data, new data shows better results in this case.

Table 3. Confusion Matrix with Adam Optimizer

		Prediction Class		
		Early Bright	Healthy	Late Blight
Actual Class	Early Bright	11	1	0
	Healthy	0	9	0
	Late Blight	0	0	11

Based on table 3, it shows that the prediction results from the model on testing data show better results. In this case, the model predicts that 11 images are predicted to be in the Early Blight class and 9 images are included in the Healthy class. then 11 images were predicted in the Late Blight class and 1 image was not predicted correctly.

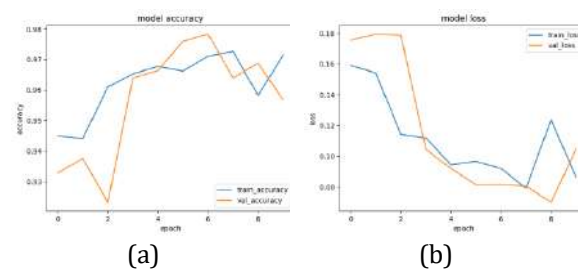


Figure 5. (a) Accuracy graph (b) Loss graph

Figure 5 shows the performance graph of loss and accuracy results from the Adam optimizer with an epoch value of 10. If you look at the graph, the training and validation accuracy continues to increase but is less stable, whereas with the loss graph, the training loss value and validation loss value experience an unstable decrease.



Figure 6. Image classification and prediction results with Adam Optimizer

The model generated from the classification results is used for image prediction. These images are Early Blight, Healthy and Late Blight classes. Based on Figure 6, the classification results show that there are many images that were predicted correctly and there are accuracy values for the predicted images.

2. Comparison of Epoch and RMSprop Optimizer

The following is an iteration with epoch 10 and 20 using RMSprop optimizer.

Table 4. Comparison Epoch and RMSprop Optimizer

Epoch	Accuracy	Loss
10	0.9753	0.1096
20	0.9679	0.0916

Based on Table 4, the results of the epoch iteration can be seen by using the Adam optimizer which produces different accuracies, namely the accuracy at epoch 10 is 97.053% with a loss value of 0.1096, then epoch 20 is 96.79% accurate with a loss value of 0.0916, so it can be seen that from the two epochs got the best accuracy at 10 epochs.

From the results of the confusion matrix shown in Table 5, it can be explained that based on Table 4, the results of predicting the model on new data testing data show better results in this case.

Table 5. Confusion Matrix with RMSprop Optimizer

Actual Class	Prediction Class		
	Early Bright	Healthy	Late Blight
Early Bright	10	0	1
Healthy	1	5	0
Late Blight	0	1	15

Based on Table 5, it shows that the prediction results from the model on testing data show better results. In this case, the model predicts that 10 images are predicted to be in the Early Bright class and 5 images are included in the Healthy class. then 15 images were predicted in the Late Blight class and 3 images were not predicted correctly.

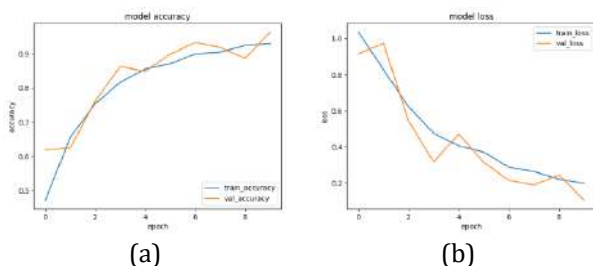


Figure 7. (a) Accuracy Graph (b) Loss Graph

Figure 7 shows the performance graph of loss and accuracy results from the RMSprop optimizer with an epoch value of 10. The training and validation accuracy values continue to increase, while in the loss graph, the training loss values and validation loss values experience a steady decline.

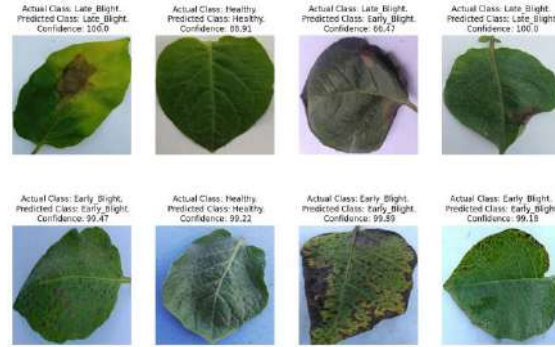


Figure 8. Image classification and prediction results with Adam Optimizer

The model generated from the classification results is used for image prediction. The images are from the Early Blight, Healthy, and Late Blight classes. Based on Figure 8, the classification results show that there are many images that were predicted correctly and there are accuracy values for the predicted images.

3. Accuracy Comparison Results

The following is a comparison used to determine the best model from all optimizers that have been trained. The following are the results of each CNN model with the best accuracy based on the optimizer and epoch.

Tabel 6. Accuracy Comparison Result

No	Optimizer	Epoch	Accuracy	Loss
1	Adam	10	0.9506	0.1403
2	RMSprop	10	0.9753	0.1096

Based on Table 6, it can be seen that using the Adam optimizer with 10 epochs produces an accuracy of 95.06% with a loss value of 0.1403, then the RMSprop optimizer using 10 epochs produces an accuracy of 97.53% with a loss value of 0.1096. So it can be concluded that using the RMSprop optimizer with 10 epochs produces the highest accuracy.

CONCLUSION

Based on the discussion explained in the previous chapter, it can be concluded that the classification of potato leaves using the CNN architecture, the CNN model can identify types of potato leaf images, Early Blight, Healthy, and Late Blight. By using the RMSprop optimizer and the softmax activation function implemented in the CNN architecture, potato leaf image classification with 10 epoch iterations obtained the highest accuracy value of 97.53% and the lowest loss value of 0.1096.

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ELECTRICITY MANAGEMENT SYSTEM WITH TECHNOLOGY INTERNET OF THINGS

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Abstract—The increasing global demand for electricity has put a strain on energy resources and raised concerns about environmental sustainability. To address these challenges, the integration of modern technologies is crucial. This research presents a study on the implementation of an Electrical Energy Management System (EMS) using Internet of Things (IoT) technology. The proposed system aims to optimize electrical energy usage, enhance efficiency, and reduce the environmental impact. The EMS employs IoT devices and sensors to monitor and collect real-time data on electricity consumption in office buildings. Through data, the system can identify patterns and anomalies in energy consumption, allowing for informed decision-making and proactive energy management strategies.

Keywords: Electrical Energy Management System, Energy Saving, Internet of Things, IoT.

Intisari—Permintaan global yang semakin meningkat terhadap listrik telah menimbulkan tekanan pada sumber daya energi dan menimbulkan kekhawatiran tentang keberlanjutan lingkungan. Untuk mengatasi tantangan ini, integrasi teknologi modern menjadi hal yang sangat penting. Penelitian ini menyajikan studi tentang implementasi Sistem Manajemen Energi Listrik (SMEL) yang menggunakan teknologi Internet of Things (IoT). Sistem yang diusulkan bertujuan untuk mengoptimalkan penggunaan energi listrik, meningkatkan efisiensi, dan mengurangi dampak lingkungan. SMEL menggunakan perangkat dan sensor IoT untuk memantau dan mengumpulkan data secara real-time tentang konsumsi listrik di gedung perkantoran. Melalui analisis data, sistem ini dapat mengidentifikasi pola dan anomali dalam konsumsi energi, memungkinkan pengambilan

keputusan yang berbasis informasi dan strategi manajemen energi yang proaktif.

Kata Kunci: Sistem Manajemen Energi Listrik, Penghematan Energi, Internet of Things, IoT.

INTRODUCTION

Electrical energy is one of the basic needs that is very important for human life today, almost all human activities are related to electrical energy (Kastutara, 2022). Electricity as a source of energy has an important function not only as a source of lighting energy but also as a source of supporting energy in carrying out daily activities. Electrical energy sources currently have the existence of being able to support various forms of operational activities, be it lighting, communication and information facilities, education, transportation, health, household activities and many other activities (Sudarti, et al., 2022). The electrical energy management system is a system implemented to save electrical energy. In general, current electrical energy management systems are implemented manually, both for controlling and monitoring electrical devices (Rizal & Ardian, 2019).

There are many dangers caused by electric current, one of which is the danger of fire caused by an increase in temperature that exceeds limits. In electrical installations, the danger of fire can be caused by excessive loads on conductors, switches, machines, equipment, etc., if the current value is too high, excessive heat development occurs. The connection between conductors or conductors and other installation components is less than perfect, thus allowing broken contacts to occur which will trigger sparks. This poor insulation condition will

result in a short circuit current between the conductors and also a ground connection current between the current from the conductor to the ground. These currents result in a local increase in extra heat. Placement of electrical machines and equipment without calculation, such as placing electric motors in narrow, closed areas without ventilation.

Basically, the danger of electricity threatens three things or objects. First, it threatens humans, which is the most serious threat, humans can die because of electricity and that cannot be paid for by anything. The second is threatening the house or building. This second threat is no less serious and if the house or building catches fire then the losses suffered usually reach large numbers. The third is threatening other goods, especially electronic goods. This threat can be said to be the lightest threat because if the electronic goods are damaged or burned, the losses suffered will not be as serious as the losses caused by the first and second threats (Kamuihkar, et al., 2022).

A total of 17,768 fire cases occurred in Indonesia throughout 2021, with 5,274 of them caused by short circuits or around 45 percent. Meanwhile, non-fire rescue operations reached 79,559 times. This means that the incidence of non-fire rescues is almost 5 times higher than rescues due to fire. The flow of electric current through the body has different levels of consequences depending on the strength of the current, length of contact, voltage, body resistance, area of the body in contact. If you are shocked by an electric shock of 1 mA there is no serious impact, but if you are shocked by an electric current of more than 10 mA it can result in illness. and damage to the skin and even result in muscle spasms, while electric currents above 100 mA 50 Hz AC will damage body organs such as the heart and risk death. Research on animals, namely mice, shows that the maximum current that touches the mouse's body with a voltage of 220 Volts (AC) is between 110-128 mA, the mouse will die in less than an hour after being shocked by electricity for 60 seconds. The main problem is that ordinary people only know about electricity from the consequences that arise when electrical energy is used, such as lights that turn on, refrigerators that can cool food, air conditioners that can reduce room temperature.

So in conditions like this it is necessary to provide education about electrical energy with the main material presented being easy to understand, such as how electricity is generated, transmitted, distributed and utilized in everyday life. Furthermore, what is more important is education about the dangers of electricity for humans, containing material on standardizing electrical equipment, standardizing the design of electrical

installations, the risks of accidents caused by electricity that must be avoided and handling victims after electric shock (Putra, et al., 2022).

Ensuring the safety of electricity consumption is crucial in preventing accidents or damage to electrical equipment that can lead to financial losses and even endanger human safety. Careless actions in electricity usage, such as using electrical appliances beyond their capacity, improper cable installation, or using damaged equipment, can result in fires or electrical short circuits. One of the fires that occurred at home was caused by an electrical short circuit. Sourced from data from the DKI Jakarta Provincial Central Statistics Agency, information was obtained that 65.82% of fires that occurred in Jakarta were caused by negligence in the use of electricity (Shaid, 2023). One of the causes of electrical short circuits is manual control of electrical devices. Thus, automation of electrical control is an effort to suppress fires caused by excessive use of electrical loads.

Energy conservation is also a critical issue considering the limited energy resources and their environmental impacts. Excessive electricity consumption without considering efficiency can lead to resource wastage. Therefore, energy-saving efforts need to be taken seriously to alleviate pressure on energy resources. Automatic control of electrical power needs special attention. The application of technology to home automation must be able to guarantee the safety, security and comfort of life at home and reduce negative environmental impacts (Azizi & Arinal, 2023).

Until now, the Internet is known as a network that connects people and information. However, the Internet has now developed far from its original concept, where not only computers and telephones can be connected, but objects or things around us can also send and receive data. The Internet of Things (IoT) is an evolution of the Internet where objects can be identified and connected to each other via the Internet. It is estimated that it will include 26 billion objects and connect 4 billion people by 2025. This development will create many opportunities and opportunities from different sides. human life. However, like the Internet and other technologies, IoT will impact users and society at large.

Internet of things or also known as IoT is an advanced technology that has a concept that aims to expand and develop the benefits of continuously connected internet connectivity. connecting objects around us so that daily activities become easier and more efficient, which really helps all human work. The importance of the internet of things can be seen by its increasing application in various areas of life today. According to the RFID (Radio Frequency

Identification) identification method, the term IoT is classified as a communication method, although IoT can also include other sensor technologies, wireless technology or QR (Quick Response) codes. The term "Internet of Things" consists of two main parts, namely Internet which connects and regulates connectivity and Things which means an object or device. Simply put, you have "Things" that can connect to each other to collect data and send it to the Internet. This data can also be accessed by other "Things" as well. where certain "Things" have the ability to send data over a network wherever you are and without any interaction from human to human or from human to computer device (Selay, et al., 2022).

Internet of Things or IoT, is a concept/idea whose aim is to expand the benefits of internet network connectivity that is fully connected and can be connected to devices, machines and other physical objects by using networks, sensors and actuators to obtain data and manage it, so that machines can collaborate and act according to new information obtained independently (Nahdi & Dhika, 2021).

The goal of IoT is to change the way we live today by making smart devices around us to perform everyday tasks. Smart home, smart city, smart transportation, smart infrastructure and others are terms used in relevance to IoT (Mantik, 2022).

By leveraging IoT, users can remotely access and control electrical appliances through applications on their mobile devices. This aids in optimizing energy usage and ensuring that electrical appliances only operate when necessary. For instance, room heaters or coolers can be scheduled or adjusted based on operational schedules or environmental conditions automatically, avoiding energy wastage when rooms are unoccupied.

Furthermore, the use of sensors and smart devices within the IoT system allows real-time monitoring of energy consumption in various areas. Data collected from these IoT devices can be analyzed to identify inefficient consumption patterns and provide recommendations for energy conservation. Users can also receive notifications or alerts in case of abnormal energy consumption or potential safety risks, such as short circuits or electrical leaks. IoT (Internet of Things) has become an increasingly widely used technological concept. Both for industrial and commercial purposes. With the presence of IoT (Internet of Things), several electronic components such as sensing facilities and control facilities such as servo motors and other devices can be controlled automatically as long as the device is connected to the Internet (Ikwan & Djaksana, 2021). Current technological developments

in the field of electronics have made human thinking increasingly advanced in the application of electronic devices. One thing that has been developed is electronic technology that allows remote control of home electronic devices using Internet of Things technology. Internet of Things (IoT) technology is a concept that aims to expand the benefits of always-on Internet connectivity. IoT can combine physical and virtual objects through the use of data collection and communication capabilities (Akbar Gumilang, et al., 2022).

By integrating IoT into the electricity management system, users gain better control over energy management and avoid power wastage. Additionally, an IoT system connected to a smart grid infrastructure can serve as a bridge to incorporate renewable energy sources, such as solar and wind power, into the existing electricity grid. This contributes to enhancing overall efficiency and sustainability in electricity consumption. An Internet of Things (IoT)-based electrical energy monitoring system that is connected to a website is one of the solutions for increasing capacity, efficiency, and convenience in carrying out electrical energy audits as an effort to conserve electrical energy (Aditya, et al., 2023).

Djabesmen Alia Building whose main focus is on building management owned by PT Djabesmen, the building is named Alia Building with 8 floors located in Gambir, central Jakarta. The building manager of Alia Building is a division led by the Department Head. The main task of the building manager is serving the needs of tenants which includes technical and non-technical services.

In the Alia Building there is a canteen located in the backyard area of the building, electricity is used freely without any restrictions and is not in accordance with the rental fee, apart from that, excessive use of equipment and unsafe installations can result in potential fires due to increased load. Therefore, the use of an electrical energy management system with internet of things technology in the Alia building canteen can be a solution:

1. Monitor electricity usage in the canteen which has not been measured;
2. Limit the use of electrical equipment with excessive power which results in energy waste; and
3. Prevent the danger of fire due to short circuits in installations and equipment.

By making tools with IoT technology and using web-based applications it is possible to control electrical equipment in the canteen area. This research was conducted from April 2023 to July 2023.

MATERIALS AND METHODS

Electricity energy management system is a web-based application that is used to control electronic equipment so that it can minimize wasteful use of electricity and prevent the danger of fires caused by electricity.

NodeMCU ESP8266 is an open source IoT-based platform. Consists of hardware in the form of System On Chip ESP8266. Currently NodeMCU has undergone 3 upgrades. The device we use is NodeMCU version 3 (V1.0) which has better capabilities than the previous version (Manullang, et al., 2021). The NodeMCU ESP8266 has integrated Wi-Fi capabilities, making it perfect for IoT projects that require a wireless connection. This allows these devices to connect to Wi-Fi networks, communicate with other devices, and send data to servers or cloud platforms. The NodeMCU ESP8266 is often used because of its ease of programming. The platform has great community support and many code examples are available for various projects.

The design of an electricity energy management system with IoT technology uses the NodeMcu ESP8226 board with the ESP 12E. NodeMcu ESP8226 is an open source IoT platform. Nodemcu is a tool used as a microcontroller to process data. This data is obtained from the PZEM 004T sensor which sends data in the form of voltage, current and power to the electronic equipment to be measured and displayed on the LCD.

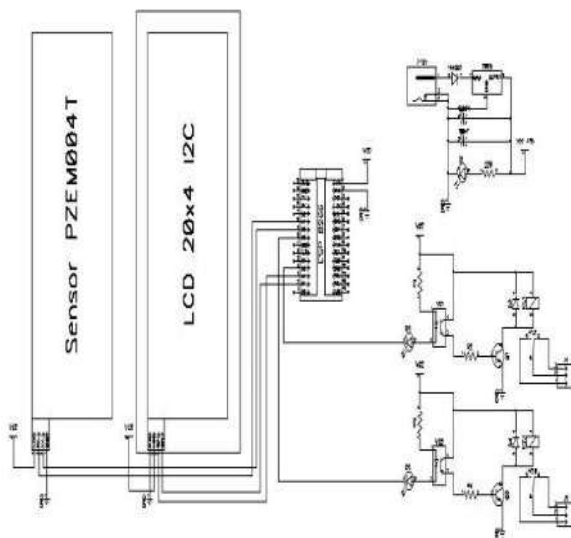


Figure 1. Sensor Circuit Schematic

ESP8266-DevKitC is a small-sized ESP8266-based development board produced by Espressif. All of the I/O pins of the module are broken out to the female pin headers on both sides of the board for easy interfacing. Developers can connect these pins to peripherals as needed.



Figure 2. ESP8266-DevKitC

The PZEM-004T sensor is a sensor that can measure current, voltage, power and energy from AC power. This sensor outputs with serial communication. If we want to connect with Arduino, the communication used is serial communication.



Figure 3. PZEM-004T

PZEM-004T is a sensor that can be used to measure Root Mean Square (RMS) voltage, RMS current and active power which can be connected via Arduino or other open source platforms. The physical dimensions of the PZEM-004T board are 3.1 × 7.4 cm. The pzem-004t module is bundled with a 3mm diameter current transformer coil which can be used to measure a maximum current of 100A (Anwar, et al., 2019).

To calculate the percentage of sensor accuracy, the equation is used

$$\% \text{Akurasi} = \left(\left(1 - \frac{\text{NilaiSensor} - \text{NilaiAlatukur}}{\text{NilaiAlatukur}} \right) \times 100\% \right) \dots (1)$$

IoT (Internet of Things) architecture refers to the structure and design of interconnected devices, networks, and systems that enable the exchange of data and information between physical objects and the digital world. It encompasses the various components, protocols, and layers that make up an IoT ecosystem.

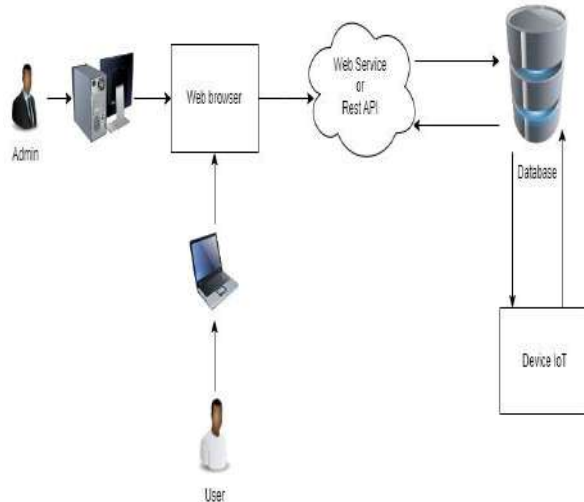


Figure 4. IoT Architecture

RESULTS AND DISCUSSION

On this occasion the author did some testing on the tool. the first is testing the accuracy of the PZEM 004T sensor against industrial standard measuring instruments, testing the tool against each individual load in the form of an electronic device, and testing control and monitoring of electricity on the SMEL WEB application (www.smel.web.id).

At this testing stage the author uses 2 measuring instruments that have industry standards as follows:

- a. Digital Clamp Meter Kyoritsu type KEW 2007R and Clamp Meter MT87 Digital Clamp Meter are used to measure current (Ampere); and
- b. Digital Multimeter SANWA type CD800a Digital Multimeter is used to measure Voltage (Volts).

PZEM 004T sensor accuracy test results data shown in the following table:

No	Electrical Load	Voltage (Volt)		
		Multi Meter	PZEM 004T	Accuracy (%)
1	Refrigerator	224.2	224.5	99.8
2	Electric Stove 1	221.3	221.4	99.9
3	Electric Stove 2	229.1	229.2	99.9
4	Rice Cooker	221.1	221.2	99.9
5	Water Heater	230.2	230.4	99.9
6	Showcase	231.4	231.7	99.8

The table 1 shows the average accuracy level of the PZEM 004T sensor compared to a multimeter for measuring voltage on several electronic devices is 99.98%.

Table 2. Current Accuracy Calculation

No	Electrical Load	Current (Ampere)		
		Pliers Ampere	PZEM 004T	Accuracy (%)
1	Refrigerator	0.70	0.74	94.3
2	Electric Stove 1	11.1	11.3	98.2
3	Electric Stove 2	7.5	7.7	97.3
4	Rice Cooker	1.3	1.39	93
5	Water Heater	4.4	4.43	99.3
6	Showcase	1.4	1.53	90.7

The table 2 shows the average accuracy level of the PZEM 004T sensor compared to the ampere pliers for measuring current in several electronic devices is 95.4%.

Table 3. Power Accuracy Calculation

No	Electrical Load	POWER (Watt)
		PZEM 004T
1	Refrigerator	165
2	Electric Stove 1	2.439
3	Electric Stove 2	1.769
4	Rice Cooker	307.6
5	Water Heater	1.017
6	Showcase	266

From the testing process, it can be concluded that the sensor voltage gets an average measurement accuracy = 99.98% and for current the average measurement accuracy = 95.4%.



Figure 4. IoT Architecture

The following picture is an electrical energy management system that has been installed in the Alia building canteen.

Table 4. Power Accuracy Calculation

No	Loads	Voltage (V)	Current (A)	Power (Watt)	Energy (kWh)
1	Refrigerator	224.5	0.74	165	0.66
2	Electric Stove 1	221.4	11.03	2439.6	9.75
3	Electric Stove 2	229.1	7.7	1769	7.07
4	Rice Cooker	221.2	1.39	307.6	1.23
5	Water Heater	230.4	4.3	1017	4.06
6	Showcase	231.7	1.4	266	1.06

This testing process to find out how good and consistent this tool is in monitoring the use of electrical energy. For testing the tool with a load it is carried out for 4 hours per tool, monitored in real time via the web application or directly via the LCD.

CONCLUSION

At the end of this research, the Electrical Energy Management System implemented in the Alia Building Canteen has made a significant contribution to more efficient and controlled electrical energy management. With the existence of an Electric Energy Management System, the use of electrical energy in the canteen can be monitored directly via a web application or via cell phone. If the canteen is not operating, the building manager can turn it off using this system so as to minimize the danger caused by electricity.

The ability to control electrical energy via the website in real time has opened the door for Alia Building Managers to monitor and manage electrical energy more effectively. Although this research also reveals several shortcomings that need to be considered in further development.

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CLASSIFICATION OF RICE TEXTURE BASED ON RICE IMAGE USED THE CONVOLUTIONAL NEURAL NETWORK METHOD

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Abstract—There are several types of rice that are commonly sold in rice stores. Many people, especially millennials, are not familiar with the different types of rice such as IR42 rice, Pera rice, sticky rice, and Pandan Wangi rice. Therefore, digital image processing techniques are needed to help analyze the types of rice to help people know what kind of rice they are going to buy at the market. The method commonly used in image processing for image classification is the convolutional neural network (CNN) method. Currently, CNN has shown the most significant results in image classification. This research used a dataset of 1560 rice images. The data was divided into two sets (training data and validation data) with an 80:20 ratio. The accuracy obtained by the CNN model using InceptionV3 for the rice data was 95.7% with a loss of 0.123. The Android application developed in this research achieved an accuracy of 83,4% based on the testing results calculated using the confusion matrix.

Keywords: android, classification, CNN, InceptionV3, rice.

Intisari—Ada beberapa jenis beras yang biasa dijual di toko beras. Saat ini banyak masyarakat khususnya generasi milenial yang belum mengenal berbagai jenis beras. Oleh karena itu, diperlukan teknik pengolahan citra digital untuk membantu menganalisis jenis-jenis beras. Metode yang umum digunakan dalam pengolahan citra untuk klasifikasi citra adalah metode convolutional neural network (CNN). Saat ini CNN telah menunjukkan hasil paling signifikan dalam klasifikasi gambar. Penelitian ini menggunakan dataset sebanyak 1560 citra padi. Data dibagi menjadi dua set (data pelatihan dan data validasi) dengan perbandingan 80:20. Akurasi yang diperoleh model CNN menggunakan InceptionV3 untuk data beras adalah 95,7% dengan loss 0,123. Aplikasi Android yang dikembangkan pada penelitian ini mencapai akurasi sebesar 83,4%

berdasarkan hasil pengujian yang dihitung menggunakan confusion matrix.

Kata Kunci: android, klasifikasi, CNN, InceptionV3, beras.

INTRODUCTION

Indonesia is one of the countries with the highest level of rice consumption per capita in the world. The reason for the high consumption of rice in Indonesia is due to the basic culture of eating rice in Indonesian society, where food is considered incomplete if there is no rice even though carbohydrate needs have been met through other food sources. Consumer demand in this case can vary from one individual to another. (Yusuf, et al., 2018). In rice shops, there are generally several varieties of rice that are often sold, such as IR42 rice, Pera rice, sticky rice, and Pandan Wangi rice. However, currently, there are still many people, especially millennials, who are not familiar with these various types of rice. Therefore, research was conducted to study and introduce various types of rice to the public (Ma'arif, et al., 2022). In classifying types of rice, humans have limitations in perceiving it through the sense of sight, considering the diversity of shapes and types of rice on the market (Emalia, 2020). Therefore, it is necessary to use digital image processing techniques to help analyze rice types more accurately (Trisnawan & Hariyanto, 2019). The method used is a convolutional neural network (CNN) with the InceptionV3 architecture (Nisa et al., 2020).

A convolutional neural network (CNN) is a method that is often used in image processing for image classification purposes (Saraswita & Sukemi, 2020). CNN is an algorithm belonging to the field of deep learning and is a development of the Multi-Layer Perceptron (MLP) model. Until now, the CNN method has shown very significant results in image

classification (Kusumaningrum, 2018). In this era, smart devices such as smartphones have a very important role in everyday life (Fikri, 2023), especially Android-based smartphones. Android is a collection of software that includes an operating system, middleware, and major applications for mobile devices (Khairul, et al., 2018).

In research entitled Classification of Rice Varieties Using Artificial Intelligence Methods (Cinar & Koklu, 2019). Using a dataset taken by yourself using a box with a camera at the top so there is no light from outside and avoids shadows. The types of rice used were Osmanic and Cammco rice, each image of which was subjected to morphological feature extraction and obtained 7 features, namely area, perimeter, MajorAxisLength, MinorAxisLength, Eccentricity, convexArea and extent. With these features, models are created using LR, MLP, SVM, DT, RF, NB and k-NN machine learning techniques and performance measurement values are obtained. The success rate in classification was 93.02% (LR), 92.86% (MLP), 92.83% (SVM), 92.49% (DT), 92.39% (RF), 91.71% (NB), 88.58% (k-NN). If we look at the success rate results, it can be said that the research has achieved success.

Then from research entitled Classification of Rice Types Using the Convolutional Neural Network Method in MobileNET Architecture (Jauhari, 2022). The types of rice used in this research were IR64, sticky, basmathi, red and black rice. The entire dataset uses RGB color images (three color channels) and is resized to 224x224 pixels according to the input in the MobileNetV1 architecture. The training results of the MobileNet architecture on a good dataset is 1.0 and the validation accuracy value is around 0.9333. Meanwhile, in the bad dataset, the training accuracy was 1.0 and the validation accuracy value decreased to 0.6889. Then the training results on the Android device for each rice in 5 tests under 3 different light conditions, namely Basmathi Rice, Black Rice and Red Rice, achieved 100% accuracy in all light conditions. Rice IR 64 has accuracy results reaching 80% for white light, 60% for yellow light, and 100% for a mixture of white and yellow light. Glutinous Rice has accuracy results reaching 80% for white light, 100% for yellow light, and 80% for a mixture of white and yellow light.

Classifying types of rice with machine learning presents several challenges. One major hurdle is the quality and quantity of data, having insufficient or imbalanced data can lead to inaccurate results. Balancing model accuracy with interpretability, adapting to varying environmental conditions like lighting, and ensuring real-time processing and scalability are deployment challenges.

Those researches have shown that we can classify rice with images. With the advantages offered by Android smartphones and the Convolutional Neural Network (CNN) method, which is one method that is often used in image processing for image classification purposes (Peryanto et al., 2020), I plan to develop an Android-based application that can classify rice texture based on the image of the rice used with CNN and transfer learning from InceptionV3. Hypothetically this application will be able to run a machine learning model with a convolutional neural network method using transfer learning with the InceptionV3 architecture.

MATERIALS AND METHODS

The following is the framework for the research to be carried out:

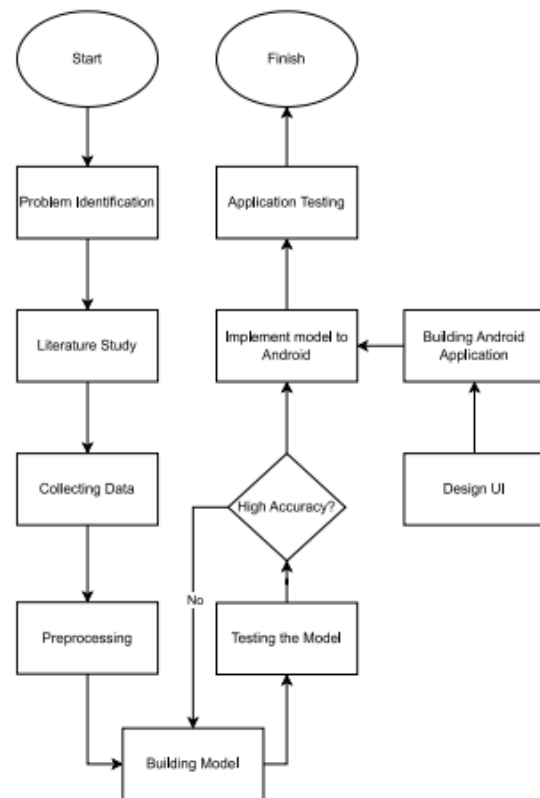


Figure 1. Research Design

Problem identification is the first stage carried out by researchers, namely classifying the texture of rice based on the rice used by distinguishing it into two classes, namely fluffier rice and pera rice. The literature study aims to study previous research that has the same topic as this research. In conducting this research, the author studied convolutional neural network methods, image classification, and Android application design from literature studies that she took.

This research uses photographs for the data collection method. The image data used in this research was obtained and taken manually using a smartphone camera. Image data is taken by placing an object (rice) on a black base and then photographing it at a distance of approximately 25 cm. There are two classes of rice images, consisting of fluffier rice and pera rice. Sample data can be seen in the Figure 2. The images taken are equal to 780 images per class (pulen and pera), so the total dataset is 1560 images and the test data for the model testing and the application testing will be taken separately from those datasets.



Figure 2. Samples of Rice Images

For training data, 80% of the total images will be taken, and 20% will be used for evaluation data. Next, the training data will be resized. Resizing is carried out to equalize the size of the image to 480 x 480. The resulting image that has been equalized in size will undergo image augmentation such as rotation_range, width_shift_range, shear_range, horizontal_flip, vertical_flip, and fill_mode to increase data variations for model training. Next, the model was built using the transfer learning method with the InceptionV3 architecture (Tsang, n.d.) with weights from the Imagenet dataset.

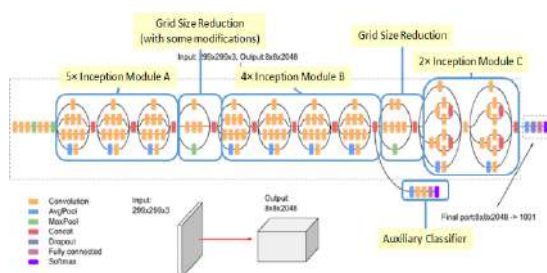


Figure 3. Inception V3 Architecture

An important part of InceptionV3 is the Inception module. This is a basic structure that allows feature extraction efficiently and at multiple scales. Each Inception module consists of several parallel convolution branches with different filter sizes, such as 1x1, 3x3, and 5x5 (Dahiya et al, 2020). The results of each branch are combined and passed to the next layer. This allows the network to

capture patterns at different scales, making it highly effective for recognizing patterns in images of varying sizes. Also, pre-trained InceptionV3 models, trained on large datasets like ImageNet, are readily available. Transfer learning, where a pre-trained model is fine-tuned for a specific task with a smaller dataset, is a common practice (Raffel et al, 2020). Using a pre-trained InceptionV3 model as a starting point often results in faster and more accurate training for specific image classification tasks.

The model will train for approximately 50 epochs with a checkpoint. After that, model testing was carried out. Model testing is carried out with the same test data that has not been seen by either the model or the tester. The model that has been created will be tested for accuracy, recall, precision, and the f1-score of the convolutional neural network model that has been formed.

Then we start designing the interface of this application, which will be created using the Figma application. After making the design in Figma, the design will be made in Android using Android Studio with an XML base and the Kotlin programming language. This research was made based on Android, with Android Studio as the IDE and Kotlin as the programming language. The design stage for this application is represented using the unified modeling language (UML), which consists of use cases and activity diagrams.

After the model has been tested and the interface is complete, the model will be converted into TensorFlow Lite format, namely (.tflite), and quantization will be carried out, where the file size of the TensorFlow Lite model will be reduced. After that, use the extension from Android Studio to import the model into Android.

The final stage is application testing, which is carried out in real-time to obtain evidence that the application runs smoothly and the results of the classification match the scanned image.

RESULTS AND DISCUSSION

The data used in this research consists of images of fluffier rice and pera. The types of rice used for this research are those that are often sold in markets, namely fragrant pandan rice and ramos rice, which are representatives of fluffier rice. Meanwhile, for pera rice, use IR42 rice. Data collection was carried out by researchers by photographing rice in conditions with bright lighting, using a black base, with the rice object spread evenly, and with the camera height set at around 25 cm at a perpendicular angle to the rice object. The total data collected was 1560 images, consisting of 780 images of fluffier rice and 780 images of pera rice.

At the training stage, image preprocessing will be carried out, namely resizing, rescaling, rotation_range, width_shift_range, shear_range, horizontal_flip, vertical_flip, and fill_mode, in order to increase the variety of data to be trained.

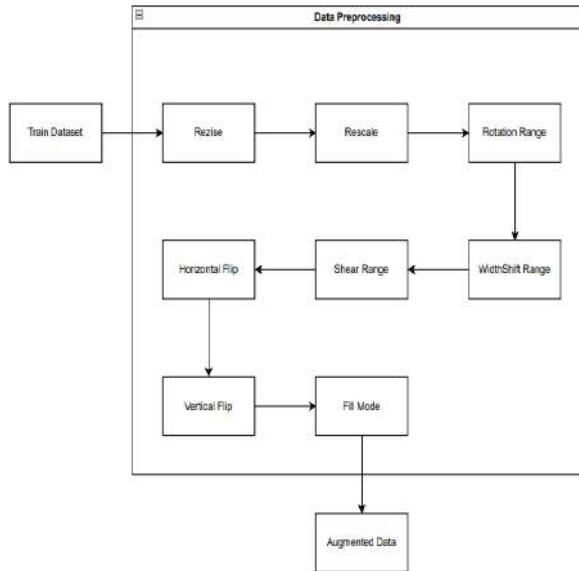


Figure 4. Data Preprocess

The dataset will change the size of the image to 480 x 480 pixels, then rotate it by 45 degrees, shift the width by 25%, tilt the image plane in the horizontal or vertical axis by 25%, flip the image horizontally and vertically, and fill in the pixel gaps automatically. whole to the nearest pixel.

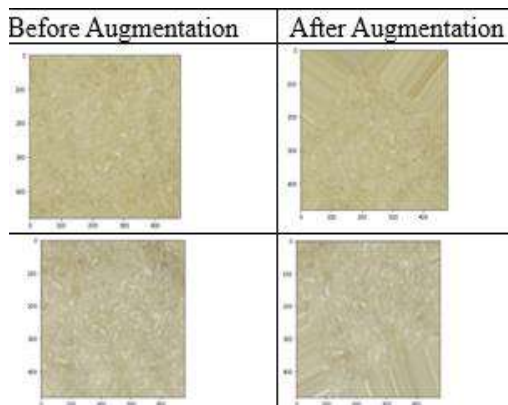


Figure 5. Results of Data Augmentation

Data augmentation here means that in the process of training, the dataset will have more varieties of images, such as flip, rotate, shift width, etc. So it will be more likely to learn the images with some noises inside.

The initial step in designing this model involves dividing the data into training and validation sets using an image data generator. In this stage, researchers divided the data in a ratio of

80% for training and 20% for validation, using a batch size of 8.

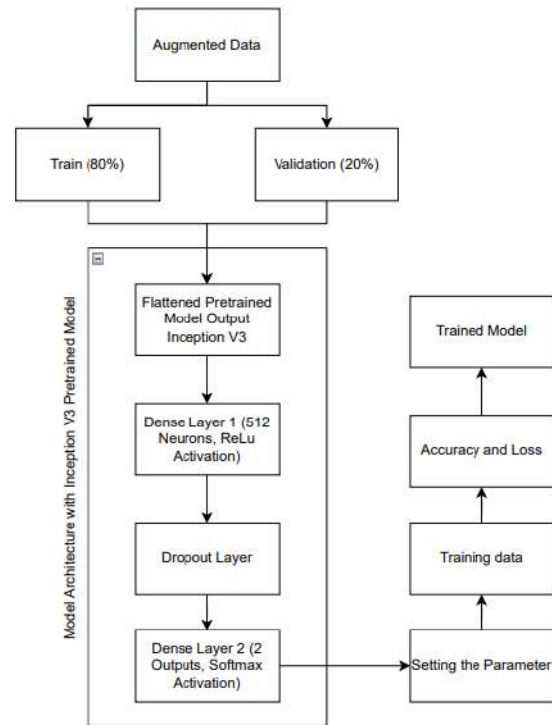


Figure 6. Model Architecture Design with Inception V3 Pre-trained Model

After a lot of trial and error, the researcher only added 2 dense layers and 1 dropout layer to the flattened pre-trained model output from Inception V3. This is because the pre-trained model itself already has good results because the weights that are in the pre-trained model using ImageNet dataset are helping the new model to learn new images. After that, the training process is carried out using a previously prepared model, with a total of 50 epochs. During the training, the process will stop if the accuracy reaches a value of 0.95 or more and the loss reaches a value of 2 or less. The model will be saved to the specified directory because the EarlyStop and ReduceLRonPlateau functions have been applied. After training was complete, the researcher visualized the training data, which included accuracy, val accuracy, loss, and val loss, to see the visualization of the model that had been trained.

The initial value of the training results with training data is good, namely 0.85 for training data and 0.75 for validation data. The training data continues to increase as the epoch progresses. The final value of accuracy for the training data is 0.957, and validation data accuracy is 0.878. Meanwhile, the loss graph obtained by the model also looks good from each epoch to a decrease, with the final result being that the loss for the training data is 0.122 and the loss for the validation data is 0.2822.

The model testing stage is carried out with a test dataset that is not included in the training process. There are 10 pictures, including 5 pictures of fluffier rice and 5 pictures of pera rice. The calculation results from testing 10 images, such as precision, recall, f1-score, and accuracy values, are all 0.8.

At this stage, the researcher used features from Android Studio, which can easily import Tflite models. Starting by creating a new folder containing the TensorFlow Lite model, we are given instructions on how to use the model. Instructions regarding using the model can be found in the models folder named 'ml'.

After importing the model, the model can be used when the predict button is pressed. Therefore, it is necessary to create a function that will be executed when the button is pressed to make predictions and produce output in the form of classified types of rice. However, in order to classify the images, they must match the model's desired characteristics. Here, the model expects the image to be a tensor image with a size of 480x480x3.

The output of the model is a float array containing two numbers. Then create a function of the two numbers, whichever index is greater. If the 0th index is greater than the 1st index, then the rice is included in the soft rice category; if vice versa, then the rice is included in the fluffier rice category.

The output of the model is a float array containing two numbers. Then create a function of the two numbers, whichever index is greater. If the 0th index is greater than the 1st index, then the rice is included in the soft rice category; if vice versa, then the rice is included in the fluffier rice category.

		Asli	
		Pulen	Pera
Prediksi	Pulen	3	0
	Pera	1	2

Figure 7 Confusion Matrix

From the test data carried out with real-time images, it can be calculated using a confusion matrix, such as

a. Precision

$$\text{precision} = \frac{TP}{(TP+FP)} \dots\dots\dots(1)$$

$$\text{precision} = \frac{3}{(3+1)}$$

$$\text{precision} = 0.75$$

b. Recall

$$\text{recall} = \frac{TP}{(TP+FN)} \dots\dots\dots(2)$$

$$\text{recall} = \frac{3}{(3+0)}$$

$$\text{recall} = 1.0$$

c. F1-Score

$$f1 \text{ score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \dots\dots\dots(3)$$

$$f1 \text{ score} = 2 \times \frac{(0.75 \times 0.75)}{(0.75+0.75)}$$

$$f1 \text{ score} = 0.857$$

d. Accuracy

$$\text{accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \dots\dots\dots(4)$$

$$\text{accuracy} = \frac{(3+2)}{(3+2+1+0)}$$

$$\text{accuracy} = 0.834$$

CONCLUSION

Based on the analysis and discussion in the previous section, researchers can conclude that convolutional neural networks can be applied to rice images using new test data and produce a high level of accuracy using the InceptionV3-imagenet architecture. The experiments that have been carried out, showed that the amount of data, hidden layers, and dropout layers inside the model is significantly influence the results of the model created.

This research also revealed that the application developed was successful in using machine learning model and identifying both types of rice texture, namely fluffier and springier. The model accuracy for the training data is 0.957, and the validation data accuracy is 0.878. For the application, the accuracy is 0.834. Apart from that, this application also has a good prediction speed, which is around 1 second. In the experiments carried out, it was found that taking a good image for prediction means taking an image at a distance of about 5 cm from the object. Apart from that, the size of this application is also quite affordable, at only 224 megabytes, and it can be run on an Android cellphone with at least 3 GB of RAM.

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REAL TIME DETECTION OF CHICKEN EGG QUANTITY USING GLCM AND SVM CLASSIFICATION METHOD

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Abstract— A common problem currently being faced in the chicken egg production home industry is difficulty in counting the number of eggs. Currently, calculating the number of eggs is still done manually, which is less than optimal and prone to errors, so many entrepreneurs often experience losses. The manual system currently used also has the potential for this to happen. The use of technology on an MSME scale among laying hen breeders has not been widely adopted, this is due to limited access and understanding of technology. One alternative solution to deal with this problem is to build a real-time computerized system. The system that will currently be built in this research uses GLCM feature extraction and the SVM classification method. This system will detect egg production via CCTV cameras and will be stored in a database to be displayed on the website. The advantage of this system is that egg entrepreneurs can monitor chicken egg yields in real time. The results of trials that have been carried out using GLCM feature extraction and the SVM classification method in calculating the number of eggs using the SVM method with a polynomial kernel are highly recommended for use in this research because it can achieve 95% accuracy.

Keywords: Automation, Chicken Egg, GLCM, SVM

Intisari—Permasalahan umum yang sedang dihadapi pada home industri produksi telur ayam saat ini yaitu mengalami kesulitan di dalam menghitung jumlah telur. Saat ini perhitungan jumlah telur masih dilakukan secara manual, dimana hal tersebut kurang optimal serta rentan terjadi

kesalahan sehingga banyak pengusaha sering mengalami kerugian. Sistem manual yang digunakan saat ini juga berpotensi terjadinya. Penggunaan teknologi pada skala umkm di peternak ayam petelur belum banyak diadopsi, hal itu disebabkan oleh akses dan pemahaman pada teknologi yang masih terbatas. Salah satu solusi alternatif untuk menangani permasalahan tersebut adalah dengan membangun sistem yang terkomputerisasi secara realtime. Sistem yang saat ini akan dibangun pada penelitian ini menggunakan ekstraksi fitur GLCM dan metode klasifikasi SVM, sistem ini akan mendeteksi produksi jumlah telur melalui kamera CCTV dan akan disimpan pada database untuk ditampilkan pada website. Keunggulan dari sistem ini yaitu pengusaha telur dapat memantau hasil telur ayam secara realtime. Hasil uji coba yang telah dilakukan menggunakan ekstraksi fitur GLCM dan metode klasifikasi SVM dalam menghitung jumlah telur penggunaan metode SVM dengan kernel polinomial sangat direkomendasikan untuk digunakan pada penelitian ini dikarenakan dapat mencapai akurasi 95%.

Kata Kunci: Otomatisasi, Telur Ayam, GLCM, SVM

INTRODUCTION

The egg-laying chicken farming business is one of the poultry farms that is important to pay attention to because this business is able to provide employment opportunities not only limited to rural areas but also in urban areas. To stabilize and strengthen the laying hen farming business, farmers

must make improvements in various aspects including production, management and marketing aspects. Currently, UMKM scale farms are managed conventionally, this is due to limited access and understanding of technology. Conventional management is prone to fraud and often causes errors.

With the development of increasingly advanced technology, innovation is needed in UMKM egg-laying chicken farms that are able to calculate the number of egg production in real time and can make it easier for business owners to monitor the number of egg production every day. It is important to have a system that can provide real-time information to business owners, with real-time information being able to predict egg production in order to fulfill supplier orders.

Apart from that, business owners can also monitor chicken productivity, where chickens that are no longer laying eggs can be moved to another place to save feed. System development trials will be carried out at one of Min's father's small-scale home industries in Gampong Blang Buloh, Blang Mangat District, Lhokseumawe City, North Aceh, where based on initial observations that have been made so far, the calculation of the number of chicken egg production and egg grouping is still done manually by employee. However, due to the large number of eggs, errors often occur in calculating the eggs before they are distributed, so many suppliers cannot be sure of their orders.

The system for calculating the number of egg production in real time is one of the object recognition concepts, where the system can recognize objects by mapping objects that have gone through a previous training process. Object recognition is one area of research that can be applied in various fields such as (Sandy et al., 2019) real-time height measurement, (Rizal, Girsang, et al., 2019) face recognition, (Sandy et al., 2023) real-time recognition of 3D geometric objects. Several previous studies regarding chicken egg detection can be seen in table 1.

Table 1. Several studies on chicken egg detection that have been carried out

Author	Data/sample	Method	Category	Results Study
(Cirua et al., 2020)	Egg Chick taken by camera	Connected Component Labeling algorithm, Threshold process,	System intelligent, processing image, segmentation	Results test try to show that the object picture egg is very influenced by size

Author	Data/sample	Method	Category	Results Study
(Fadchar & Delacruz, 2020)	Take picture egg chicken five (5) days old (150 images)	Segmentation threshold limit, conversion RGB color, Network Nerves Imitation	Processing Image, Segmentation, Classification	image, intensity light, and distance taking image. Predictive models own accuracy whole by 97%. Predictive models own ratio more mistakes_ low compared to with predictions made_ through a manual candling process
(Narushin et al., 2020)	40 items egg chicken fresh purchased from Woodlands Farm, Canterbury and Staveley's Eggs Ltd, Coppel, England	Hügelschäffer model, contour egg chicken And count repeat variable the geometry	Non-destructive measurement System automatic	Application And its validity For measure egg
(Saifullah & Andiko Putro Suryotomo, 2021)	Egg chicken on system hatchery egg	K-means segmentation, space color L*a*b, scale	Segmentation Image, Processing Picture	K-means based segmentation room L*a*b

Author	Data/sample	Method	Category	Results Study
		gray , Histogram Equalization , morphology		color available used For stage beginning detection embryo
(Nyalala et al., 2021)	Studies other	Reviews	Classification non-destructive measurement	Overview challenge And potency trend period front in estimation size , weight , and production volume poultry
(Saifulah et al., 2022)	Chicken egg hatchery systems	K-means Segmentation, L*a*b color space, grayscale, Histogram Equalization, morphology	Image Segmentation, Image Processing	K-means segmentation based on L*a*b color space can be used for the initial stages of the embryo detection process

MATERIALS AND METHODS

A. Research Stage

In Figure 1 you can see the detection process for identifying the number of egg production that will be carried out. Starting with the stages of image acquisition using a CCTV camera, segmentation is then carried out to separate the object from the background. and cropping which functions to get the characteristics of the egg image (Yennimar et al., 2019)(Rizal & HS, 2019).

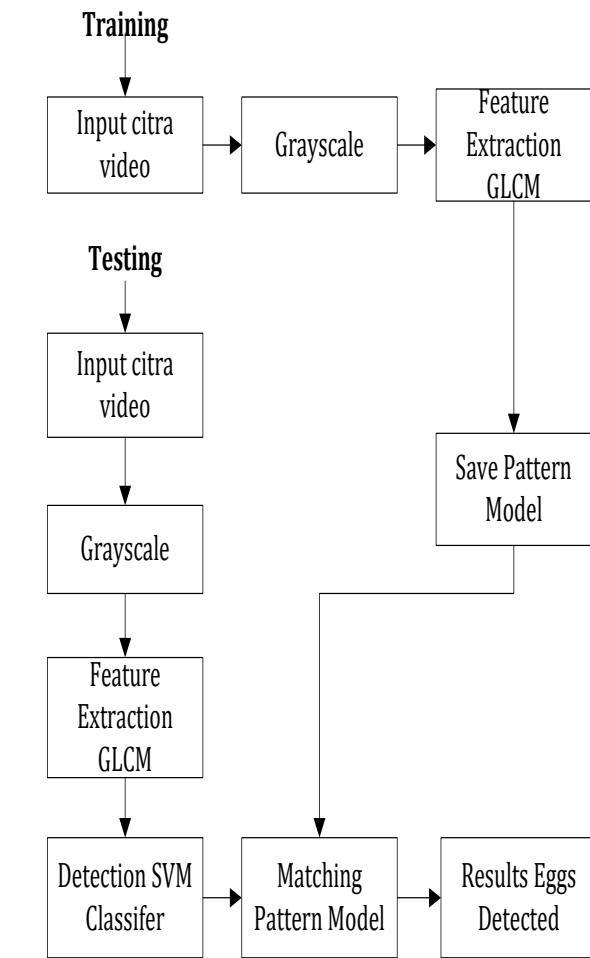






Figure 1. Framework of the Proposed Method

Next, the image will be pre-processed grayscale to make three intensity values into 1 intensity value which is useful for saving computation. Feature extraction stages using GLCM with 6 parameters, namely: Energy (En), Contrast (Ct), Entropy (Et), Variance (V), Correlation (Cr), and Homogeneity (H). The final stage of detecting the number of eggs is processed using SVM by applying 3 kernel models to deal with nonlinear data because not all data in the dataset can be separated linearly.

B. Data Collection

At this stage, data is collected using a smartphone camera with a black background. There were two types of images taken, namely images of domestic chicken eggs and images of village chicken eggs, with a total of 212 eggs. There are 106 images of domestic chicken eggs and 106 images of free-range chicken eggs. When taking pictures, the room lights are turned off to produce the desired image. The image results (Rizal et al., 2020), can be seen in Table 2.

Table 2: Image of Domestic Chicken Eggs and Village Chicken Eggs

No	Image of National Chicken Eggs	Village Egg Image
1		
...
106		

RESULTS AND DISCUSSION

Pre-processing

At the image pre-processing stage, the first step is to resize the egg image. At this stage, the image is resized to 250 x 250 pixels. Next, the image is converted from RGB (Red, Green, Blue) format to grayscale image. As an illustration, for example, we take the pixel values in the n5.jpg image which have RGB values of 354, 225, and 81, then these values are converted to a grayscale image with the following procedure:

$$\text{Grayscale} = (0,299 R \times 354) + (0,857 G \times 225) + (0,114 B \times 81) = 307$$

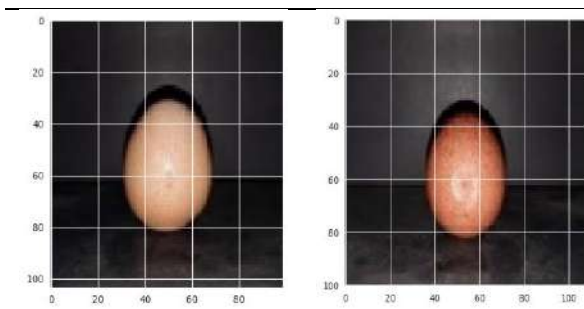


Figure 2. Pre-processing process

In Figure 2, you can see an illustration of the pre-processing process that has been applied to all images, which have been resized to 255x255 pixels (Dewantoro et al., 2022). The next stage is the implementation of the dataset training process, and the results can be observed in Figure 3.

Segmentation

In this segmentation process, the algorithm used is k-means clustering. At this segmentation stage, the original image is divided into three cluster objects that have different pixel values and contrast. Next, the pixel value is used as the cluster center or centroid, where the number of centroids is the same as the number of clusters, namely 3. Table 3 provides a description of the cluster center values in the n5.jpg image (Saifullah et al., 2021).

Table 3: Cluster Center Values

Cluster 1	2.527630238255	3.7577124027142
	25	5
Cluster 2	73.82991700829	23.175182481751
	92	8
Cluster 3	111.1531701192	32.093220338983
	272	1

Table 3, which describes the cluster center values above, refers to the cluster center values in one of the images, namely n5.jpg. Next, the value of each pixel in the results of the K-means Clustering algorithm is labeled according to the corresponding cluster. K-means Clustering returns the index corresponding to the respective cluster.

Next, each pixel value is summed according to its cluster, producing three cluster objects. After these objects become three cluster objects, the number of pixels in each cluster area is calculated. Then, the lowest value from the cluster is taken and used as the resulting clustered data value. The results are then converted into a binary image. The next process is masking, where the binary image is multiplied by a grayscale image. After segmentation with K-means Clustering is complete, the results can be used in the texture feature extraction process.

Feature Extraction

After the segmentation stage is complete, the feature extraction process continues. The method used for feature extraction is GLCM (Gray Level Cooccurrence Matrix)(Rizal, Gulo, et al., 2019). The resulting segmentation image is processed by considering the features and direction in GLCM. There are three features from the Gray Level Cooccurrence Matrix that are used for feature extraction, namely contrast, homogeneity and energy. The distance taken in this process is d=1, with degrees 450, 900, and 1350.

Table 4: Gray Level Co-Occurrence Matrix Contrast Values

Citra	Kontras 45°	Kontras 90°	Kontras 135°
1	0.38180029 3543653	0.2974136546 18474	0.3768648892 75979
2	0.36873598 8129224	0.275 24497991967 9	0.369 18759374848 8
3	0.23289946 9363397	0.1812048192 77108	0.2345446041 19288
4	0.38828405 9934517	0.2833734939 75904	0.3767036015 54814
5	0.21631909 1627554	0.1485301204 81928	0.224 44799277431 0
6	0.4 758310349 83307	0.3753574297 18876	0.453 18623893163 0
7	0.23606070 8698247	0.1868915662 65060	0.2396412961 08127
8	0.24286705 0531443	0.1965622489 95984	0.2439315494 91137
9	0.31289817 9061628	0.2106666666 66667	0.3130272092 38561
10	0.22538346 1557072	0.1503935742 97189	0.218 80292253350 8

Classification

Data that has gone through the feature extraction process will then be directed to the classification stage. In this stage, the method used is SVM (Support Vector Machine)(Muhathir et al., 2019). Classification is carried out by comparing training data and test data in a ratio of 60:40. Details of the composition of this data comparison are explained in Table 5.

Table 5. Training and Testing Data Distribution Structure

Datasets	Image of the National Chicken	Image of Kampung Chicken
Training	200	200
Testing	600	600
Validation	200	200

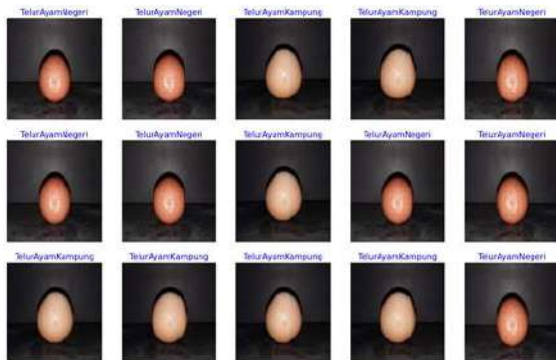


Figure 3. Training dataset for detection of domestic chicken eggs and free-range chicken eggs

Figure 3 is an illustration of the training dataset process which aims to obtain image characteristics to differentiate domestic chicken eggs from village chicken eggs, the results of classification using SVM, which can be seen in Figure 4.

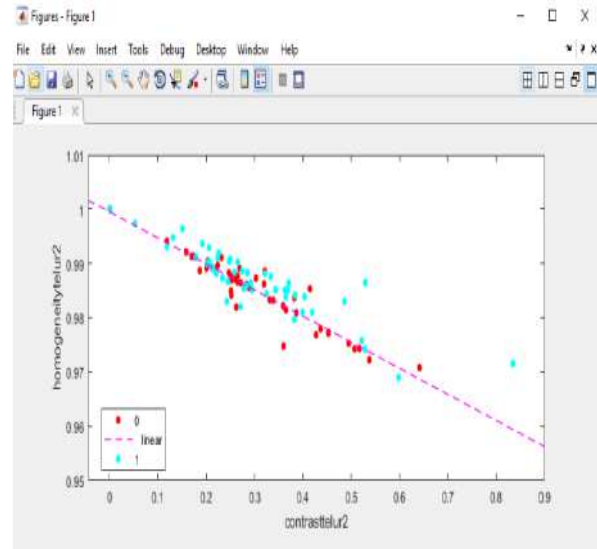


Figure 4. Hyperplane in Support Vector Machine

Data for domestic chicken eggs in class 0 is depicted with red dots, while data for free-range chicken eggs in class 1 is depicted with light blue dots. The hyperplane lines used in the representation are presented as pink dotted lines. After seeing the distribution of this data, the system will display the value of the confusion matrix, which will indicate how many predictions are correct or incorrect. Confusion matrix is used to calculate accuracy, recall and precision values. The evaluation results of this model can be found in Table 6.

Table 6. Model Evaluation Results

	Accuracy	Precisio n	Recall	F1- Score
Kernel	0.833333	0.84615	0.833333	0.885
Linear	333	3846	333	714
Kernel	0.95	0.86363	0.95	0.904
Polyno mial		6364		762
Kernel	0.891666	0.85489	0.891666	0.895
RBF	6665	5105	6665	238

Table 6 shows the results of the model evaluation carried out in this research using GLCM feature extraction and the SVM calcification method. In testing using a linear kernel the results were accuracy: 0.83, precision: 0.84, recall: 0.83 and F1 score: 0.88. Meanwhile, testing using the polynomial kernel results are Accuracy: 0.95, Precision: 0.86, Recall: 0.95 and F1 Score: 0.91 and

testing using the RBF kernel results are Accuracy: 0.89, Precision: 0.85, Recall: 0.89 and F1 Score: 0.89.

CONCLUSION

This research aims to detect the number of eggs based on their type. Based on the results of tests carried out, the system was only able to detect eggs from domestic and free-range chickens. The highest accuracy results in this research were using a polynomial kernel with an accuracy of 0.95 (95%). The results of this research show that the SVM method with a polynomial kernel is highly recommended for use because it can achieve 95% accuracy. To get even better results in the future, increasing the number of chicken egg samples is highly recommended to increase the best accuracy which will then be tested using deep learning with architectures such as Mo-bileNetV2, VGG16 ADAM, ADAGRAD, and SGD, etc.

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COMPARISON OF KNN, NAIVE BAYES, DECISION TREE, ENSEMBLE, REGRESSION METHODS FOR INCOME PREDICTION

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Abstract—Using the income classification dataset, we performed data analysis with the help of data mining to gather interesting information from the available data. Currently, data processing can be done using many tools. One of the tools that we use for data processing is the orange application. By using the dataset we looked at the welfare level ranging from marital status, school, gender, and from all fields related to income ranging from sales, to daily life to find out the income earned by employees or workers from several countries such as the United States, Cambodia, United Kingdom, Puerto-Rico, Canada, Germany, Outer US (Guam-USVI-etc). The purpose of this analysis is to determine the hourly income in one week that can affect the income classification. The classification technique uses various classification models, namely the K-Nearest Neighbor (KNN) algorithm model, Naive Bayes, Decision Tree, Essemble Method and Linear Regression algorithm. The results of the analysis based on the test results of various algorithm models can be concluded that the best algorithm model for measuring workers' income is to use the Naive Bayes Decision. Analysis of variables based on Hours-per-Week and Capital-Gain affects Income Classification which determines whether the income earned is more than 50 thousand/50 K and the analysis results in a prediction of a person's income level.

Keywords: algorithm method comparison, data mining, income classification, orange.

Intisari—Menggunakan dataset income klasifikasi, kami melakukan analisis data dengan bantuan data mining untuk mengumpulkan informasi menarik dari data yang tersedia. Saat ini pengolahan data dapat dilakukan dengan menggunakan banyak tools. Salah satu tools yang kami gunakan untuk pengolahan data adalah aplikasi orange. Dengan menggunakan dataset kami melihat berdasarkan tingkat kesejahteraan mulai dari status pernikahan, sekolah, jenis kelamin, dan dari segala bidang yang berhubungan dengan pendapatan mulai dari penjualan, hingga kehidupan sehari-hari untuk mengetahui pendapatan yang didapat karyawan atau pekerja dari beberapa negara seperti Amerika Serikat, Kamboja, Inggris, Puerto-Rico, Kanada, Jerman, AS Terluar (Guam-USVI-dll). Tujuan dari analisis ini untuk mengetahui pendapatan per jam dalam satu minggu yang dapat mempengaruhi klasifikasi pendapatan. Teknik klasifikasi menggunakan berbagai model klasifikasi, yaitu model algoritma K-Nearest Neighbor (KNN), Naive Bayes, Decision Tree, Essemble Method dan algoritma Linear Regression. Hasil analisis berdasarkan hasil pengujian dari berbagai macam model algoritma dapat disimpulkan bahwa model algoritma yang paling bagus untuk mengukur pendapatan pekerja adalah dengan menggunakan Naive Bayes Decision.

Analisis variabel berdasarkan Hours-per-Week dan Capital-Gain mempengaruhi Income Classification yang menentukan apakah penghasilan yang didapat lebih dari 50 ribu/50 K dan analisa tersebut menghasilkan prediksi tingkat pendapatan seseorang.

Kata Kunci: data mining, klasifikasi pendapatan, orange.

INTRODUCTION

There are many technological advances available with computers. Computers not only help us get work done, but they can also be fun and useful tools to use. To further maximize work, internet-based technology really supports online work (Mardiani, et al., 2023).

In addition, with internet technology work is much faster and easier to complete than using traditional computers. The development of information technology has become so rapid. Internet technology connects thousands of computer networks of individuals and organizations throughout the world (Laksono, et al., 2023).

As time progresses, more and more data is needed by every human being. With so much data available, it becomes increasingly difficult to analyze the data (Indriyawati & Khoirudin, 2019). Therefore, humans need the help of data mining to collect interesting information from available data. By using data mining, you can discover interesting knowledge from large amounts of data stored in databases, data warehouses, or other information storage places (Karo, et al., 2020).

One of the important problems in data mining is classification which involves finding rules that limit given data into predetermined classes. In the data mining domain where trillions of data are used, the execution time of existing algorithms can take a long time. Therefore, we need automatic tools that can help us convert this huge amount of data into information (Djamaludin, et al., 2022).

Several previous studies were used as references. Research with the Orange Application is known to be beginner-friendly and the data analysis process is simple (Hozairi, et al., 2021). This is because Orange does not require coding skills to operate it. You just have to choose the existing features according to your needs. Let's say you want to create a classification or regression model. You just need to add a widget like KNN or Naive Bayes and provide data to the model by connecting the data source to the model by drawing connecting lines (Ratra & Gulia, 2020).

The next reference research is regarding research with Orange as a comprehensive component-based framework for machine learning and data mining. Oranges have been used in science, industry, and learning. Scientifically, it is used as a testing platform for new machine learning algorithms, as well as to apply new techniques in genetics and other fields of bioinformatics. Orange provides an overview using data visualization, classification, evaluation, unsupervised learning, association, visualization using Qt, and prototype implementation are some of the well-known features of Orange (Wiguna & Rifai, 2021).

The next reference research regarding data prediction can be carried out using several algorithms, including the K-nearest neighbor algorithm and the Neural Network algorithm. In this research, we will compare how the K-Nearest Neighbor and Neural Network algorithms predict household income in the census conducted in Bereau (Priyanti, 2019).

Processing results using orange data mining using income classification dataset with target variable income $\leq 50k$ and income $> 50k$ based on 14 features consisting of Age, Workclass, Fnlwgt, Education, Education-num, Marital-status, Occupation, Relationship, Race, Sex, Capital-gain, Capital-loss, Hours-per week, and Native country.

This research uses quantitative research because we analyze data based on the numbers that we process and then we can conclude the algorithm (Marutho, 2019).

MATERIALS AND METHODS

This research uses quantitative methods related to numbers or nominal values which are often used in survey research or opinion polls. Qualitative methods focus on natural, real, subjective and interactive events with participants. Mixed methods are a combination of quantitative and qualitative techniques so that the results are complete, useful, balanced and informative (Marinu, 2023).

The data collected for this research is primary and secondary. Primary data is taken from the Kaggle website, namely the Income Classification dataset <https://www.kaggle.com/datasets/lodetomasi1995/income-classification>. The secondary data collection techniques in this research were obtained from online media and other sources. Literature studies will be used by researchers to describe and analyze the data that has been collected which is related to this research (Dachi, 2023).

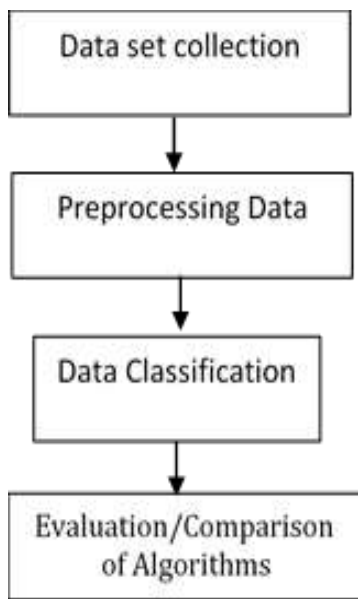


Figure 1. Research Stages

The stages in this research consist of 4 stages, namely dataset collection, data testing, prediction process, performance evaluation and method comparison results (Susetyoko, et al., 2022).

The first step is collecting a dataset. This is done first to develop research objectives and research contributions (Yuwono, et al., 2021). Second is data testing, namely testing existing data with applications that are useful for compiling data as a source of data classification. Third is the prediction process for the results of data testing. Fourth is the process of evaluating the performance of each method tested to produce predictions using KNN, Decision Tree, Essembled Method, Naive Bayes and linear regression models (Giri, 2018). Fifth is the process of method comparison results and analyzing the method comparison results (Indrapras, et al., 2022).

RESULTS AND DISCUSSION

The following is the workflow for the income classification data set technique. Income classification, this data set is obtained from the Kaggle site and is used to present information regarding the predicted value of a group of attributes

<https://www.kaggle.com/datasets/lodetomasi1995/income-classification>.

In the data mining domain where trillions of data are used, the execution time of existing algorithms can take a long time. Therefore, we need automatic tools that can help us convert this huge amount of data into information.

From Figure 2 we can see the data table dataset. We can use the KNN method to get

predictions by connecting Preprocess with KNN, Data Sample and Predictions.

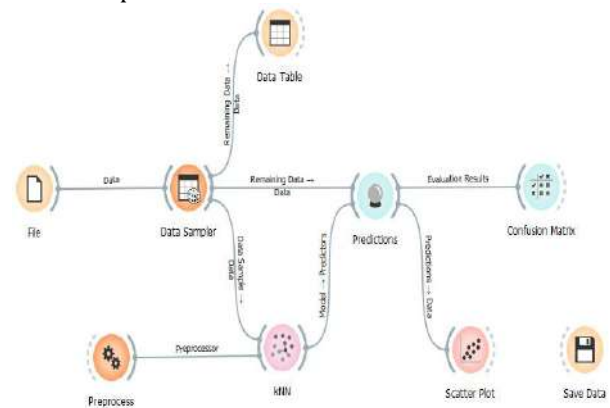


Figure 2. Workflow for the KNN Algorithm

From Figure 3 the Data Sampler is connected to the Data Table and Naive Bayes, and the test score to calculate the success rate and results of the Test and Score.

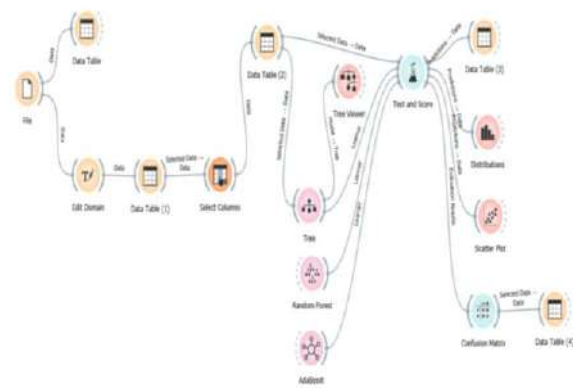


Figure 3. Workflow for the KNN Algorithm

From Figure 4, the Data Sampler is connected to Column to arrange the data domain manually, add a Data Table and connect to Tree Viewer, Data Table, Random Forest, AdaBoost, Distributions, Scatter Plot, Confusion Matrix to see the results

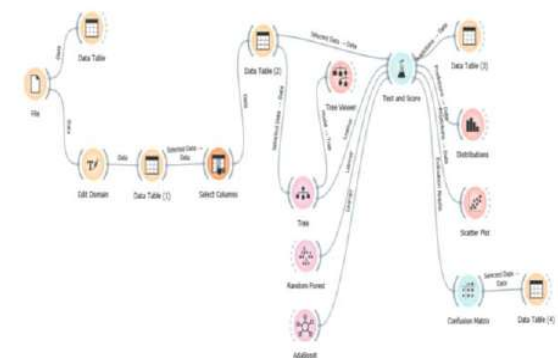


Figure 4. Workflow for Decision Tree and Ensemble Algorithms

From Figure 5, the Data Sample is connected to Column and select numeric variables as features

and capital gain as target, add the rank and correlation widgets, finally add the Test and Score & Scatter Plot widgets then connect the two to get the results from linear regression

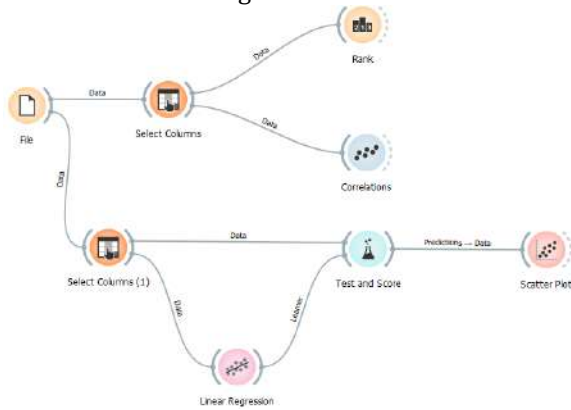


Figure 5. Workflow for the Linear Regression Algorithm

K-Nearest Neighbor (KNN)

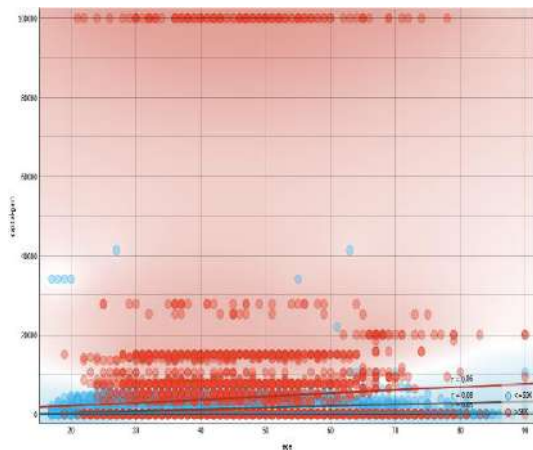


Figure 6. K-Nearest Neighbor (KNN)

The KNN model shows AUC of 84.7%, CA of 82.7%, F1 of 82.5% and Recall of 82.7%. This shows that the KNN prediction model shows good predictions seen from its AUC of 84.7%, which means that anything above 50% shows good prediction results. This means that the income analysis in the kNN model has good predictions. Then, from the results of the Confusion Matrix using the existing Train Data, it shows that KNN's prediction for Income <=50k is actually 19,967 for income <=50k. Then there is a prediction error of 2,280 because KNN predicts income >50k when the actual income is <=50k. The prediction error was 2,782 because KNN predicted income <=50k, so actual income should be >50k. Then, there are KKN predictions for actual income >50k against income >50k totaling 4,275 Data Trains.

From the Scatter Plot above, the Age and Capital-Gain variables influence Income with the

highest point being Age 78 and Capital-Gain being 99,999, entering the Income >50k class. The Age and Capital-Gain variables influence Income with the lowest point being Age 17 and Capital Gain being 0, entering the Income <=50k class. If you look at the Scatter Plot above, it is a distribution of Income with the variables Age and Capital-Gain, the relationship between these two variables to Income is, if you look at the Age, the taller or more mature a person is and the higher the Capital Gain, the Income obtained will be greater. namely above 50k. On the other hand, if you look at the lower or immature age and the lower the capital-gain, it will affect the income below 50k.

Naive Bayes

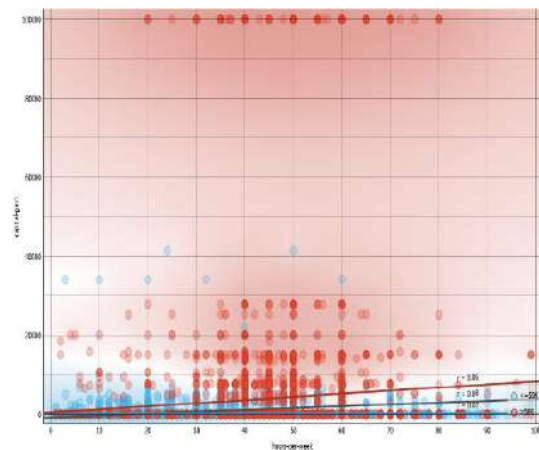


Figure 7 Naïve Bayes

The Naïve Bayes model shows AUC of 0.903, CA of 0.824, F1 of 0.831, Precision of 0.846, and Recall of 0.824. This means that the level of precision in predicting or classifying income below 50k and above 50k is above 84%. Then, the Data Table results connected to the Confusion Matrix show that the Naive Bayes prediction for Income <=50k Actual against Income <=50k is 20,751. However, there is a Naive Bayes prediction error of 3,969 because Naive Bayes predicts Income >50k, the Actual Income should be <=50k and there is a prediction error of 1,750 because kNN predicts Income <=50k, the Actual Income should be >50k.

The Scatter Plot above depicts the distribution of Income with the Hours-per-Week and Capital-Gain variables. The relationship between these two variables and Income is, if you look at Hours-per Week, the higher a person's working hours, the higher the income they get, too. but because there is a Capital-Gain factor, even though you have high Hours-per Week, if the Capital-Gain is low then the Income you get will be low too. On the other hand, if the Capital-Gain is high even though the Hours-per-Week is low, the Income will be high too. If you look at the predictions for

Income Under 50k and Above 50k, you can see the distribution, on average a high Capital-Gain will have an Income Above 50k (in red) and the distribution for Income Under 50k is only spread across Capital-Gain 50,000 and below.

Decision Tree

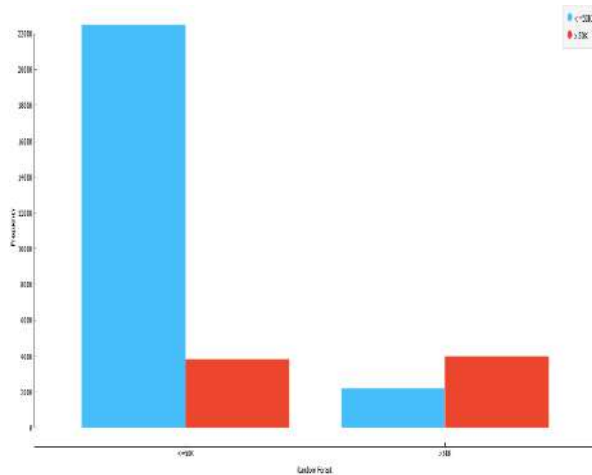


Figure 8 Decision Tree

Based on the 3 algorithm models used, namely Tree, Random Forest, and AdaBoost, the best algorithm model is Random Forest because it has the highest AUC, namely 0.821 or 82%. Meanwhile, the AdaBoost algorithm model has a result of 0.755 or 75% and the smallest is the Tree algorithm model, namely 0.673 or 67%.

The Confusion Matrix results show that the Decision Tree prediction for Actual Income Under 50k against Income Above 50k is 22,481 data. Then, there was a Decision Tree prediction error of 2,239 data because the Decision Tree predicted Income Above 50k, when the Actual Income should have been under 50k. Apart from that, there was a prediction error of 3,902 data because the Decision Tree predicted Income Under 50k, when the Actual Income should be Above 50k. The Confusion Matrix results also show that the Decision Tree prediction for Actual Income Above 50k against Income Under 50k is 3,939 data.

In Tree Viewer, the first benchmark taken is Capital-Gain. If the Capital-Gain is below 6,849 then it is in the Under 50k category and if it is above 6,849 then it is in the Above 50k category. Then the Under 50k category is divided into two based on age. If younger than 29 years, then enter the Under 50k category and if older than 29 years then enter the Under 50k category. The second Under 50k is further divided based on Education-num, if the education period is less than 12 years then it is in the Under 50k category and if it is above 12 years then it is in the Above 50k category.

In the Scatter Plot, the Age and Capital-Gain variables influence Income with the highest point Age = 78 and Capital-Gain = 99,999 Income Above 50k. The Age and Capital-Gain variables influence Income with the lowest point being Age = 17 and Capital-Gain = 0 entering the Income Under 50k class. The Scatter Plot is a distribution of Income with Age and Capital-Gain variables. If you look at the predictions for Income Under 50k and Above 50k, you can see the distribution, on average a high Capital-Gain will have an Income Above 50k (in red) and for the Income Under distribution 50k is only spread across Capital-Gains of 50,000 and under, it doesn't really look at the age, but those in the age range of 20 - 80 have high Capital-Gains, and 80-90 are in Capital-Gains under 30,000.

In the Distributions menu, the Random Forest variable influences Income where the Random Forest prediction for Under 50k predicts Under 50k with 26,383 data and Above 50 with 3,902 data. Apart from that, Random Forest Above 50k predictions show Under 50k predictions of 3,939 data and Above 50k predictions of 6,178 data.

Linear Regression

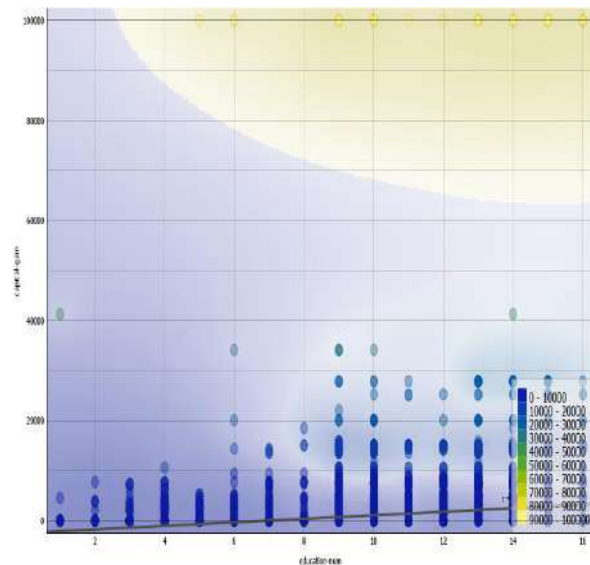


Figure 9 Linear Regression

Based on the creation of a linear regression algorithm model, in Test & Score there are MSE, RMSE, and MAE models which are values for calculating the level of Regression strength. If we use R2, the correlation between education-num data and Capital-Gain, the effect is only 1.5%. Meanwhile, if we add the house-per-week variable the effect becomes 1.9%. This means that it has increased by 0.4%, which means the level of accuracy has increased (better). Then, in the Scatter Plot, the regression points that accumulate between the x axis = Education-num and the y axis = Capital-

Gain, show that the education-num variable influences Capital-Gain. This means that the longer you study, the higher your Capital Gain. From the Scatter Plot, it can be seen that the highest point is education-num = 16 and Capital-Gain = 99,999. Meanwhile, the lowest point is education-num = 1 and Capital-Gain = 0. This means that the results of the regression analysis are, education-num influences the high and low Capital-Gain figures.

Result of Model Comparison

Based on testing various algorithm models, the comparison of test results can be seen in Table 1.

Tabel 1. Result of Model Comparison

Model	AUC	CA	F1	Precision	Recall
KNN	0.847	0.827	0.825	0.847	0.827
NB	0,903	0,824	0,831	0,846	0,824
DT	0.673	0,794	0.788	0.785	0,794
RF	0.821	0.811	0.803	0.800	0.811

Based on table 1, it can be seen that the Naïve Bayes model shows an AUC of 0.90, CA of 0.824, F1 of 0.831, Precision of 0.846, and Recall of 0.824. This means that the level of precision in predicting or classifying income below 50 thousand and above 50 thousand is above 84%

CONCLUSION

From the results of the analysis based on the results of various models ranging from kNN, Naive Bayes, Decision Tree & Ensemble Method and Linear Regression, it can be concluded that the best algorithm model for measuring income is using the Naive Bayes Decision model. This can be seen from the results of AUC, CA, F1, Precision and Recall which have values above 0.5 or above 50%, which shows that the prediction results from the Naive Bayes model are good. It can also be seen in the AUC results of the Naive Bayes model with the number 0.903 and the precision results of 0.846, which means that the prediction from the Naive Bayes model is almost close to 1 or almost accurate.

This means that it can be concluded that variable analysis based on Hours-per-Week and Capital-Gain influences Income Classification which will determine whether the Income is above 50k or below 50k. Because in this analysis our group determined the target to be Income by choosing 2 variables as a means of measuring it, namely Hours-per-Week and Capital-Gain with Numeric data.

These results can be used to predict a person's income level, and are also useful in various ways, such as determining a person's eligibility to receive financial aid programs. However, it is important to ensure that the model is accurate and

unbiased in its predictions, and that the data used is representative of the population from which it is studied.

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