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PARAMETER TUNING IN BACKPROPAGATION NEURAL NETWORKS: IMPACT OF LEARNING RATE AND MOMENTUM ON PERFORMANCE

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Abstract— *Artificial Neural Network (ANN) play a pivotal role across diverse domains, including medicine, economics, and technology, due to their ability to model complex relationships and deliver high prediction accuracy. This study systematically examines how learning rate and momentum interact in backpropagation, moving beyond isolated analysis to enhance ANN performance. A qualitative research design employing a systematic literature review was utilized, with data sourced from reputable databases covering the past 11 years. Bibliometric tools such as VOSviewer and R-Studio were applied to identify trends and patterns in the literature. The findings reveal that both learning rate and momentum significantly impact convergence efficiency and model stability. Backpropagation remains fundamental for weight adjustment in minimizing prediction errors. ANN optimization demonstrates substantial practical benefits, including enhanced treatment outcome predictions in medicine, modeling nonlinear patterns in economics, and improved image classification accuracy. However, challenges such as the curse of dimensionality, overfitting, and dependence on large datasets persist. Strategies such as regularization, ensemble methods, and sensitivity analysis present viable solutions. This study underscores the critical need to advance ANN optimization techniques and highlights the potential of interdisciplinary collaboration in addressing existing limitations and broadening ANN applications.*

Keywords: *accuracy optimization, artificial neural networks, backpropagation, learning rate, momentum.*

Intisari— *Jaringan Syaraf Tiruan (JST) memiliki peran yang sangat penting dalam berbagai bidang, termasuk kedokteran, ekonomi, dan teknologi, karena kemampuannya dalam memodelkan hubungan kompleks dan menghasilkan akurasi prediksi yang tinggi. Studi ini secara sistematis menganalisis interaksi antara laju pembelajaran dan momentum dalam proses backpropagation, serta melampaui analisis terpisah untuk meningkatkan kinerja JST. Penelitian ini menggunakan metode kualitatif dengan pendekatan systematic literature review, serta mengumpulkan data dari basis data bereputasi dalam rentang waktu 11 tahun terakhir. Alat bibliometrik seperti VOSviewer dan R-Studio digunakan untuk menganalisis tren dan pola dalam literatur. Hasil kajian menunjukkan bahwa learning rate dan momentum memiliki pengaruh signifikan terhadap efisiensi konvergensi dan stabilitas model. Backpropagation tetap menjadi elemen dasar dalam penyesuaian bobot untuk meminimalkan kesalahan prediksi. Optimasi JST terbukti memberikan manfaat praktis yang besar, seperti peningkatan prediksi hasil pengobatan di bidang medis, pemodelan hubungan nonlinier di bidang ekonomi, serta peningkatan akurasi klasifikasi citra. Meski demikian, tantangan seperti curse of dimensionality, overfitting, dan kebutuhan akan dataset yang besar masih menjadi perhatian. Pendekatan seperti regularisasi, metode ansambel, dan analisis sensitivitas menawarkan solusi yang menjanjikan. Penelitian ini menegaskan pentingnya pengembangan lebih lanjut strategi optimasi JST dan menyoroti potensi kolaborasi multidisipliner dalam mengatasi keterbatasan serta memperluas penerapan JST.*

Kata Kunci: *optimasi akurasi, jaringan saraf tiruan, propagasi balik, laju pembelajaran, momentum*

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INTRODUCTION

Artificial Neural Networks (ANN) have emerged as one of the most transformative technologies in the field of artificial intelligence, enabling advanced solutions in domains such as image classification, economic forecasting, medical diagnosis, and predictive analytics [1]. These networks are inspired by the biological processes of the human brain and have the advantage of processing complex and non-linear relationships in large data sets a capability that goes beyond traditional algorithms. By utilizing layers of interconnected artificial neurons, ANNs can learn patterns, make predictions, and classify data with incredible precision, making them an indispensable tool in modern data science and machine learning. However, achieving optimal performance in ANNs is not easy, as it requires careful tuning of various parameters. ANNs have emerged as a widely adopted method due to their ability to model complex nonlinear relationships in today's data-driven era. Training parameters such as learning rate and momentum significantly influence ANN performance, making their optimization a key focus in the development of efficient and stable models. [2].

Among the many factors that affect ANN performance such as learning rate and momentum stand out as key components in determining the convergence speed and accuracy of the network [3]. The learning rate is a hyperparameter that controls the magnitude of weight changes during training. This parameter is crucial for guiding the model toward the global minimum of the loss function. Too high a learning rate may cause the model to skip the optimal solution, while too low a learning rate may result in slow convergence. On the other hand, momentum introduces a smoothing effect by incorporating past gradients into the current weight update, thereby reducing oscillations and improving convergence stability [4]. Meanwhile, the backpropagation neural network (BPNN) serves as the backbone of the training process and enables efficient calculation of gradients through the network layers [5]. The BPNN is a supervised learning algorithm widely used for training artificial neural networks (ANNs). It functions by efficiently calculating gradients through the network layers to update the weights. By propagating the error backwards from the output to the input, the BPNN systematically adjusts the weights to minimize the loss function. These two components of the BPNN algorithm together form a synergistic framework for optimizing ANN training, but these parameters also present challenges in choosing their optimal configuration.

The combination of learning rate and momentum is essential to improve the accuracy and robustness of ANN models such as backpropagation. Selecting the right learning rate is crucial to balance convergence speed and accuracy. Momentum helps accelerate training by smoothing out fluctuations in gradient updates. At the same time, the BPNN algorithm ensures that weight adjustments are calculated accurately, thus minimizing errors in successive iterations [6]. However, suboptimal settings of these variables can lead to significant problems, such as overfitting, under-fitting, or convergence failure. For example, too high a learning rate can destabilize the training process, while poorly adjusted momentum parameters can reduce the expected benefits [7]. Moreover, the complexity of the BPNN architecture, especially in deeper networks, reinforces the importance of tuning these parameters to achieve consistent and reliable results. Therefore, a comprehensive understanding of the dynamic interactions among these components is essential for developing high-performance models capable of handling the complexity of real-world data.

BPNN have been widely applied in various fields to model complex relationships, but the training process faces challenges in determining the optimal parameters. Although many studies have explored BPNN optimization, few have systematically analyzed the combined effects of learning rate and momentum on model accuracy. This study aims to fill this gap by examining how these parameters interact to influence convergence efficiency, stability, and predictive performance. Momentum techniques, such as can enhance traditional momentum by considering a window of past gradients, resulting in better convergence rates when training more complex networks [8]. Windowed Momentum is an extension of traditional momentum that computes the average of gradients over a fixed-size sliding window to stabilize and accelerate the optimization process. *Adam Optimizer* has combined momentum with adaptive learning rate and shown superior performance in various training, especially in classification and image generation [9]. Adaptive learning rate algorithms such as *AdaGrad* and *RMSprop* can adjust the step size based on historical gradient information which accelerates convergence in sparse data scenarios [10]. Furthermore, studies show that the Adam Optimizer often outperforms Stochastic Gradient Descent (SGD) in complex tasks, although its effectiveness depends on dataset characteristics and model architecture. Backpropagation, on which ANN training is based has facilitated weight adjustment by minimizing the error gradient. Its application in complex networks has been shown to produce more accurate prediction models [8]. Few studies analyze how learning rate and momentum together improve BPNN accuracy. Most focus on each separately, missing their combined effects.

This combination of parameters has been applied in various fields, including medicine, economics, and image classification. In the medical field, BPNN are instrumental in predicting treatment outcomes, analyzing large datasets to improve personalized medicine [11]. BPNN are widely used to analyze complex patient data such as medical histories, imaging, and genetic information to predict treatment outcomes and support personalized medicine. Their ability to model non-linear patterns enables clinicians to improve diagnostic accuracy and tailor therapies to individual patient profiles. BPNN also excels in pattern recognition and aids disease diagnosis by identifying patterns in medical images such as X-rays and MRIs [12]. In economics, BPNN contributes to market forecasting and modeling economic trends through historical data analysis to support better investment decision-making. In addition, BPNNs are used in financial risk analysis, where they detect market anomalies and assess risks effectively [13]. The success in image classification further highlights the versatility of BPNNs. The technology supports facial recognition systems to enhance security measures, as well as being used in anomaly detection, identifying improprieties in images that are critical to health and security applications [14]. While these achievements are remarkable, challenges such as data privacy and the need for large datasets remain, requiring ongoing attention to ensure effective BPNN implementation.

The implementation and optimization of BPNNs face challenges such as the curse of dimensionality, overfitting, and the need for large datasets [15]. Many researchers have explored innovative strategies in addressing these issues, for example, sequential sensitivity analysis and randomized training improve model effectiveness and simplify data selection. Adaptive subspace methods have surpassed traditional sampling techniques in high-dimensional optimization and offer a high-performance alternative [16]. In addition, BPNNs have been effective in modeling complex relationships, such as evaluating the effects of training volume on athletic performance [17]. However, the gap between the potential of BPNNs and their technical challenges remains significant. Advanced approaches such as fuzzy set-based comparative qualitative analysis (fsQCA) coupled with BPNNs provide deep insight into the non-linear relationships among variables and improve model performance [18]. These methods represent a good direction to overcome existing limitations and improve the stability and effectiveness of BPNNs.

Although many studies have examined the optimization of Backpropagation Neural Networks (BPNN), there is still a lack of systematic analysis of the interaction between learning rate and momentum in improving model accuracy. Most studies tend to discuss these two parameters separately without examining their combined effects on convergence efficiency, stability, and overall predictive performance of the model. Therefore, this study specifically aims to address this gap by identifying the latest research trends and patterns that comprehensively examine the interaction between these two parameters. Therefore, this study aims to identify trends and patterns in recent research. This research is also expected to provide comprehensive guidance in selecting and optimizing BPNN parameters with a particular focus on the combination of learning rate and momentum to improve model accuracy and stability. In addition, the findings of this study are expected to contribute in overcoming the major challenges in BPNN implementation such as overfitting and curse of dimensionality.

MATERIALS AND METHODS

This research is a qualitative research with a systematic literature review (SLR) approach. This method is used to identify, evaluate, and interpret all relevant research results regarding the effect of the combination of "learning rate" and "momentum" parameters on the accuracy of the backpropagation algorithm. This approach allows researchers to systematically collect and analyze data from various relevant sources, so as to provide an in-depth understanding of this topic. The data in this study

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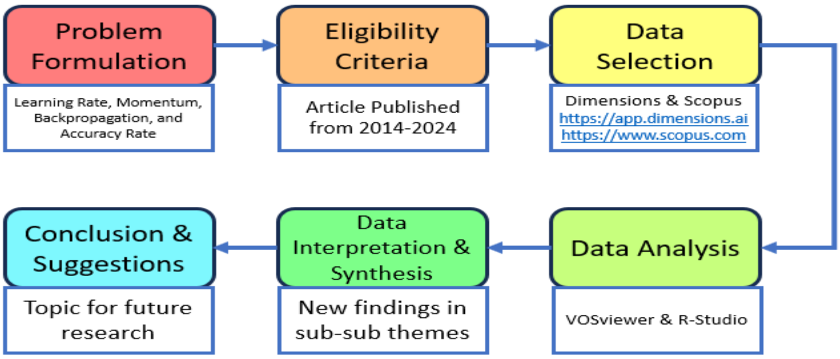
was sourced from reputable databases including Scopus (https://www.scopus.com), DOAJ (https://doaj.org), and Dimensions (https://app.dimensions.ai) with publications of the last 10 years interval to ensure the data used is current and relevant to the development of research on backpropagation. Data eligibility criteria in this study were established to ensure that only relevant and high-quality literature was analyzed. The criteria include (1) scientific articles published in reputable international journals; (2) studies that specifically discuss the parameters "learning rate" AND "momentum" AND "backpropagation" in the backpropagation algorithm; (3) publications published in the last 10 years (2014-2024); and (4) articles available in full text and in English or Indonesian. The research procedure is as shown in Figure 1.



Source: (Research Results, 2025)

Figure 1. Research procedures

Figure 1 illustrates the stages of this research, which include problem formulation, defining eligibility criteria, data selection, data analysis, data interpretation and synthesis, and drawing conclusions. In the problem formulation stage, the focus was narrowed to examine the effects of the "learning rate" and "momentum" parameters on the accuracy of the backpropagation algorithm. Eligibility criteria were established to ensure the relevance and quality of the selected studies. The data search employed specific keywords and Boolean operators such as ("backpropagation" AND "learning rate") AND ("momentum" OR "optimization") to capture relevant articles comprehensively. Searches were conducted across reputable indexed databases including Scopus and Dimensions, focusing on articles published between 2014 and 2024. After initial retrieval, the screening process involved reviewing titles, abstracts, and keywords to exclude studies unrelated to the interaction between learning rate and momentum in BPNN optimization. Further, full-text articles were assessed to ensure the inclusion criteria were met, such as relevance to parameter optimization, empirical or theoretical contributions, and availability of clear results. This systematic filtering enhanced the accuracy and validity of the data set.

The selected data were imported into VOSviewer to visualize keyword relationships and thematic clusters, while R-Studio was used for descriptive statistical analysis, including frequency counts of themes and trend analyses. The visualization and analysis outputs were interpreted to identify key variables and patterns. These findings formed the basis for discussing theoretical and practical implications regarding parameter optimization in the backpropagation algorithm. Finally, conclusions were drawn, and recommendations for future research topics were formulated.

RESULTS AND DISCUSSION

Results of Data Selection

The search results found 63,521 data that fit the research topic. Then, the results of data selection found as many as 28,365 articles that are relevant and according to eligibility criteria. Of these, 23,088 journal articles and 5,277 proceedings articles were found. The distribution of data based on the year of publication can be seen in Figure 2 which shows the development of the number of studies in the last 10 years.

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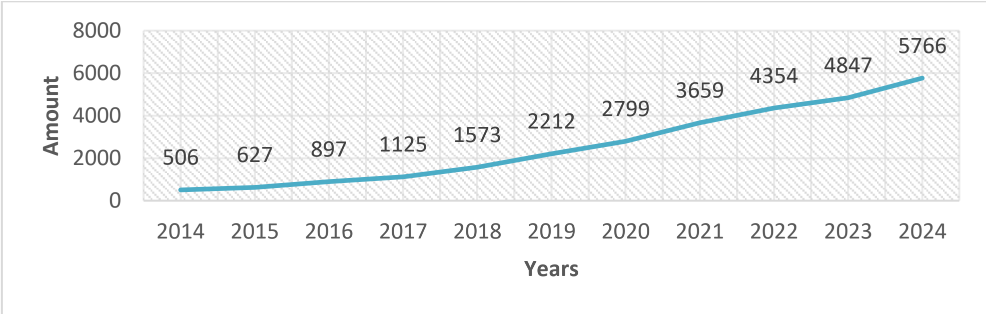


Source: (Research Results, 2025)

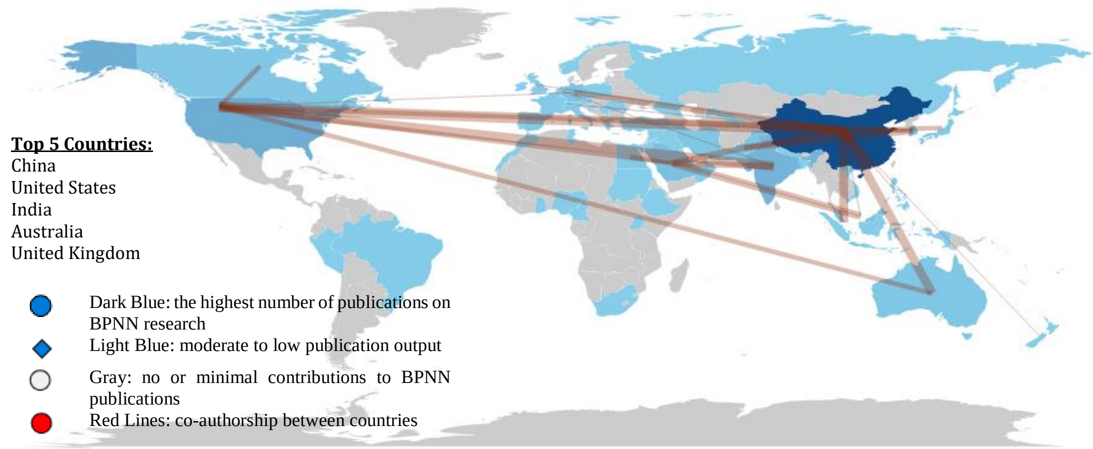
Figure 2. Publications in each year

Figure 2 shows the trend in the number of research publications over a 10-year time span, showing that in 2014 the number of publications was still very low, at 506 articles. This number slowly increased each year, but remained in moderate numbers until 2016, reaching 897 publications. In 2017 there was a significant increase with the number of publications reaching 1,125 articles. This trend continued to increase and reached 2,799 publications in 2019, indicating a growing interest in the topic. After that, the trend in the number of publications continued to increase steadily until it reached 4,847 articles in 2023 with a peak in 2024 with a total of 5,766 publications. This development reflects the increasing attention and research conducted on the topic of learning rate and momentum in the backpropagation algorithm over the past 10 years.

Trend in the number of research publications on learning rate and momentum in backpropagation algorithms from 2014 to 2024. The figure illustrates a clear upward trajectory, highlighting a shift from marginal academic attention in 2014 (506 publications) to a substantial surge beginning in 2017. This trend peaked in 2024 with 5,766 publications, reflecting a growing recognition of the critical role these hyper-parameters play in optimizing neural network training. The consistent increase suggests not only heightened academic interest but also evolving complexity and practical relevance of optimization strategies in deep learning research.

Distribution of Research in Several Countries

At this stage, we investigated the distribution of publications in several countries. Figure 3 shows that this topic has been widely researched and involves collaboration between countries in various parts of the world such as the United States, China, India, Australia, Japan, and other countries.



Source: (Research Results, 2025)

Figure 3. Countries' Collaboration World Map

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Figure 3 indicates that the high number of publications in these countries contributes to an increase in the number of citations and in-depth reviews of research results. Countries with high publication rates have a greater opportunity to increase scientific impact through works that are more frequently cited and used as references by other researchers. This shows the important role of international collaboration in enriching research related to the backpropagation algorithm and its applications [19]. Table 1 shows the 10 countries with the highest number of citations related to this research.

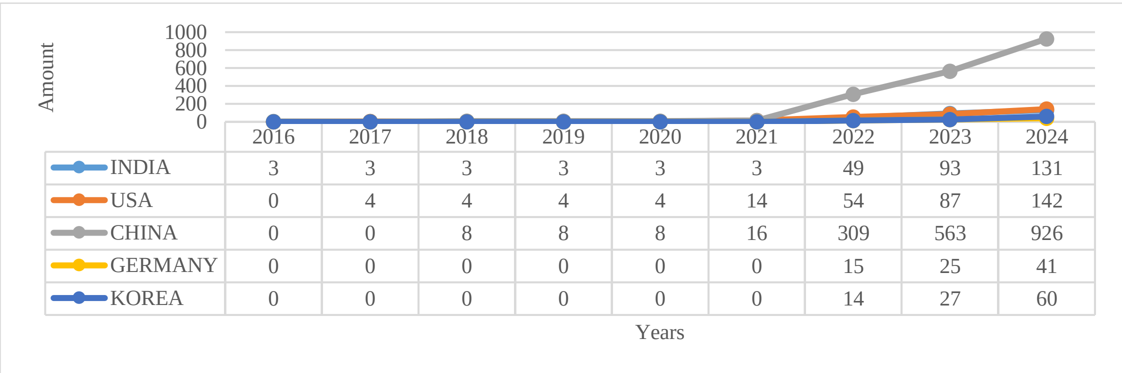
Geographic distribution of publications on backpropagation-related research and their citation impact. The figure reveals that countries with high research output, such as the United States, China, and India, also demonstrate higher citation frequencies, indicating not just quantity but also the influence of their contributions. This suggests that well-established research infrastructures and sustained publication efforts significantly enhance a country's scientific visibility. Moreover, it underscores the importance of fostering international collaboration to accelerate innovation and broaden the scope of methodological advancements in neural network optimization.

Table 1. Most Cited Countries

No	Country	Total Citations	Average Article Citations
1.	Australia	2,519	209,90
2.	China	1,811	9,10
3.	India	349	10,60
4.	USA	326	17,20
5.	Korea	260	13,00
6.	Japan	177	35,40
7.	Malaysia	166	18,40
8.	Egypt	134	22,30
9.	Spain	105	17,50
10.	Brazil	99	24,80

Source: (Research Results, 2025)

Table 1 shows that Australia is ranked first with the highest total citations of 2,519 and an average citation per article of 209.90 which indicates that articles published from Australia have a very significant level of relevance and impact in the academic community. Furthermore, China has a total of 1,811 citations, but its average citations per article is relatively low, at only 9.10, indicating that although the productivity of publications in China is high, the impact per article is not as great as other countries. On the other hand, countries such as Japan and Egypt show high average citations per article at 35.40 and 22.30 respectively, although their total citations are smaller than Australia and China. This suggests that articles from these two countries receive greater individual attention by the international research community. In addition, Korea with 260 total citations and an average of 13.00, as well as India and the US with an average of 10.60 and 17.20 citations respectively show significant levels of contribution in this research topic. Thus, Australia stands out not only in productivity but also in the quality of high-impact articles, while other countries such as Japan and Egypt show excellence in article quality on average despite lower total contributions. This trend reflects that interest in learning rate, momentum, backpropagation, and accuracy rate research is growing globally with a diverse focus between productivity and article quality in each country.



Source: (Research Results, 2025)

Figure 4. Countries' Scientific Publication Output Over Time

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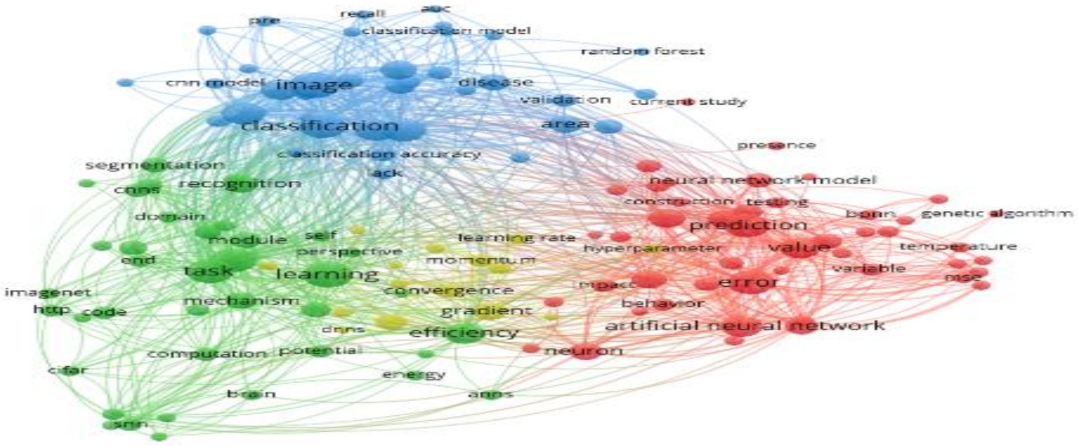
Figure 4 shows the growth trend of the number of studies in India, the US, China, Germany and Korea in the period 2016 to 2024. China showed the most significant increase, starting in 2021 with only 8 publications which then increased sharply to reach 926 in 2024. This trend shows the tremendous interest and attention to this topic in China in recent years. On the other hand, the US and India show more gradual growth. The number of studies in the US started increasing from 2022 with 14 publications to reach 142 in 2024. Similarly, India shows a similar trend with a rise from 3 publications in 2021 to 131 in 2024. Both reflect a consistently growing interest in this research topic.

Meanwhile, Germany and Korea started contributing from 2022. Germany recorded an increase from 15 to 41 publications in 2024, while Korea grew from 14 to 60 publications in the same period. This shows that although the contribution from these two countries is smaller than China, there is a growing interest in this topic. Thus, China has the most significant growth in the number of publications, while other countries such as the US, India, Germany, and Korea show a more stable growth trend towards research on the topics of learning rate, momentum, backpropagation, and accuracy rate.

International growth patterns in publications related to learning rate and momentum optimization reveal varying national research dynamics. The sharp rise in China's output suggests a concentrated national investment in machine learning development, while the steadier trends in the US, India, Germany, and Korea indicate expanding but differentiated levels of engagement. These patterns reflect how strategic priorities and research capacities shape global contributions to neural network optimization studies.

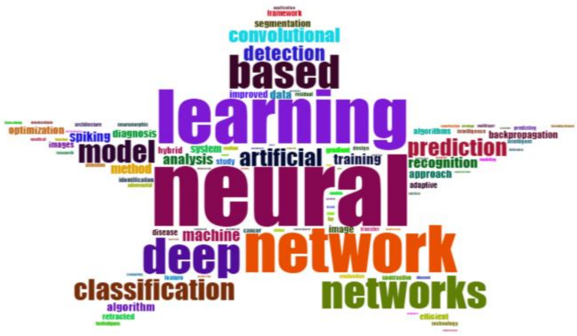
Visualization of Data

At this stage, we visualize all research results using VOSviewer and R-Studio to see the research variables and the relationship between variables. The visualization results are as shown in Figure 5.



Source: (Research Results, 2025)

Figure 5 (a). Network Visualization of data using VOSviewer



Source: (Research Results, 2025)

Figure 5 (b). Wordcloud Visualization of data using R-Studio

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Figure 5 is a visualization generated using VOSviewer and R-Studio software that shows the relationship and frequency of occurrence of relevant keywords in research related to “Learning Rate, Momentum, Backpropagation, and Accuracy Rate”. We clarify the analysis on the keywords that appear in both visualizations and have been grouped by clusters using these two software as presented in Table 2. This grouping helps identify the main topics that will be discussed further in each cluster.

Keyword co-occurrence network revealing the thematic structure of research on learning rate and momentum in backpropagation studies. The clustering patterns highlight how the field is organized around interconnected subtopics, suggesting the emergence of specialized research areas and methodological convergence. This visualization provides insight into the conceptual focus and evolving research priorities within the domain.

Table 2. Variable of data

Software	Cluster	Keywords
VOSviewer	Blue cluster	Classification, image, cnn model, classification accuracy, disease, and segmentation.
	Green cluster	Learning, momentum, gradient, efficiency, task, and convergence.
	Red cluster	Neural network model, prediction, error, value, and artificial neural network
R-Studio	Cluster 1	Neural, network, deep, dan learning
	Cluster 2	Backpropagation, momentum, training, dan optimization
	Cluster 3	Classification, detection, dan segmentation
	Cluster 4	Model, based, framework, dan approach

Source: (Research Results, 2025)

Table 2 presents the set of variables based on the clusters generated by VOSViewer and R-Studio. The blue, green and red clusters of VOSViewer reflect the focus on image-based classification techniques, learning process optimization and the development of artificial neural network-based prediction models. On the other hand, R-Studio divides the data into four clusters covering neural networks and deep learning, optimization techniques such as backpropagation and momentum, classification and segmentation, and the development of frameworks and model approaches. Each cluster will be analyzed in more detail in the following sections, taking into account the context of the data and related literature.

1. **Visualization data using VOSviewer**
   Classification and Image Analysis
   The blue cluster displays terms such as classification, image, CNN model, classification accuracy, disease, and segmentation. These words indicate a focus on image classification-based research, especially in the context of convolutional neural networks (CNNs). For example, the term disease indicates the application of CNNs in diagnosing diseases through medical image analysis. In addition, segmentation emphasizes the use of segmentation techniques to divide images into more meaningful parts, which are often used in pattern recognition and image analysis. Overall, this cluster centers on the development and application of classification methods to improve accuracy in medical image and data processing.

Learning and Optimization
The green cluster includes terms such as learning, momentum, gradient, efficiency, task, and convergence. This cluster indicates a focus on learning and optimization techniques, especially on deep learning. The terms momentum and gradient refer to optimization methods such as gradient descent with momentum that aim to accelerate the convergence of learning models. The term efficiency indicates the attention to the efficiency of the learning process, both in terms of time and computational resources. By integrating these concepts, this cluster reflects research on how to improve the learning process and produce more efficient and accurate models.

Prediction and Neural Network Modeling
The red cluster includes words such as neural network model, prediction, error, value, and artificial neural network. This cluster focuses on prediction based on artificial neural networks. Terms such as error indicate research related to analyzing model errors to improve prediction accuracy. In addition, value indicates attention to the evaluation of prediction parameters and results. This cluster underscores the importance

of building effective neural network models for various prediction applications, including economics, weather, and pattern recognition.

2. Visualization data using R-Studio

The 1st Cluster: Neural Networks and Deep Learning

Dominant terms such as *neural, network, deep,* and *learning* indicate a major focus on artificial neural networks and deep learning research. The consistent appearance of keywords like neural and deep indicates an ongoing focus on deep learning architectures and their capacity to process complex, high-dimensional data. These studies lay the groundwork for understanding how training mechanisms like backpropagation function in deeper architectures.

For this study, Cluster 1 establishes the broader ecosystem in which BPNNs operate. It provides context for why parameter tuning particularly learning rate and momentum is crucial in enabling these networks to efficiently learn hierarchical representations, minimize error, and generalize well to unseen data. This foundational understanding is necessary to explore why improper tuning of learning rate or momentum may lead to poor convergence or instability in deeper networks.

The 2nd Cluster: Optimization and Training

Words like *backpropagation, momentum, training,* and *optimization* refer to techniques for training neural networks. It reflects the primary techniques and algorithmic strategies used to train BPNNs effectively. Backpropagation remains the dominant learning mechanism, and the prominence of momentum and optimization keywords indicates a sustained interest in refining this process through hyper-parameter adjustment.

This cluster directly supports the study's research questions by highlighting the centrality of parameter tuning especially the interplay between learning rate and momentum in the literature. Research trends in this cluster provide insights into how specific combinations of these parameters accelerate convergence, prevent oscillations, and enhance generalization. It also illustrates the shift from static training configurations to adaptive and dynamic methods such as Adam or RMSprop, which often integrate momentum and learning rate control.

The 3rd cluster: Classification and Segmentation

Terms such as *classification, detection,* and *segmentation* indicate a focus on image processing tasks, such as classification of objects in images, object detection, and image segmentation. This cluster emphasizes application domains, particularly in image processing and computer vision, where BPNNs are often implemented for tasks such as object classification, medical image detection, and semantic segmentation. These domains serve as critical test beds for evaluating the performance of trained models under real-world conditions.

The significance of this cluster to the current study lies in its practical orientation. By analyzing how BPNN performance varies across different tasks, researchers gain insight into the efficacy of learning rate and momentum configurations in diverse application contexts. Moreover, the tendency of BPNNs to overfit in tasks with high data complexity reinforces the need for robust parameter optimization strategies especially those that balance fast convergence with generalization capacity.

The 4th Cluster: Model and Frameworks

Words like *model, based, framework,* and *approach* indicate attention to the development of frameworks and model approaches. Cluster 4 highlights the development of architectural innovations and methodological frameworks in neural network training. This includes the use of ensemble methods, transfer learning, and hybrid optimization strategies, often designed to improve learning dynamics and mitigate common neural network problems. From the standpoint of this study, this cluster underscores the need for structured approaches to parameter selection. It reflects a growing body of research that attempts to formalize and generalize best practices for model configuration including guidelines for tuning learning rate and momentum. Insights from this cluster may serve as theoretical support for building comprehensive optimization frameworks tailored to specific application needs or data characteristics.

The results of data analysis from VOSviewer and R-Studio show a segmented research focus into several clusters with complementary themes. Clusters from VOSviewer, such as classification and image analysis, learning and optimization, and prediction and neural network modeling illustrate

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the use of machine learning techniques, particularly ANNs, in various applications. The emphasis on image classification with CNN highlights the significance of this technique in pattern recognition, such as medical image analysis for disease diagnosis, where accuracy and segmentation play a key role. Meanwhile, the Learning and Optimization cluster reflects efforts to improve model efficiency and stability through optimization techniques such as gradient descent with momentum. On the other hand, Prediction and Neural Network Modeling highlights the focus on improving prediction accuracy through error management and parameter evaluation.

Results from R-Studio enrich this understanding by providing additional focus on the development of more efficient artificial neural networks and training techniques. Clusters such as Neural Networks and Deep Learning demonstrate the important role of hierarchical learning in understanding complex data patterns, while Optimization and Training focuses on core algorithms such as backpropagation and modern optimizations such as the Adam optimizer. This cluster not only highlights key techniques, but also challenges such as overfitting, which is a major concern in the development of reliable models and good generalization. In addition, Classification and Segmentation from R-Studio emphasizes image processing applications, where image segmentation and object detection have a great impact in fields such as medical, security, and facial recognition.

Synthesis of Data

Based on the interpretation of each cluster, we can formulate some important points as synthesized results about learning rate, momentum, backpropagation and accuracy rate according to Table 3.

Table 3. Insights from the author and research results

No	Authors	Research Insights or Variables
1	Srimamilla (2022); Solikhun & Alkhairi (2024); Saxena & Nagraj (2023); Ashawa et al. (2024); Wang et al. (2022); Singh et al. (2020); Anju & Vimala (2024); Pronunciate et al. (2018)	Application of CNNs in image classification in various fields, including medical, malware detection, and accuracy challenges on varied image sources.
2	Zhou et al. (2021); Huang (2022); Ando & Takefuji (2021); Spring & Shrivastava (2017); Liu et al. (2022)	Deep learning optimization techniques, including gradient descent, momentum, SGD, and adaptive variants to speed up training and improve stability.
3	Aval et al. (2014); Chen et al. (2018); Ounajim et al. (2021); Beck et al. (2022); Calvo-Pardo et al. (2020); Yin et al. (2024); Madhiarasan & Louzazni (2022); Daydar (2021); Ekayanti et al. (2022)	Application of BPNNs in medical prediction and economic forecasting, as well as techniques to improve model accuracy and stability through regulation and sensitivity analysis.

Source: (Research Results, 2025)

Table 3 reveals three major thematic concentrations in recent literature on neural network-based learning systems, particularly in relation to learning rate, momentum, and model accuracy. The first group of studies emphasizes the application of Convolutional Neural Networks (CNNs) in diverse domains, ranging from medical imaging to cybersecurity, reflecting CNNs' versatility in handling complex image classification tasks. However, these studies also underscore persistent accuracy challenges, especially when dealing with heterogeneous image sources. The second cluster focuses on deep learning optimization strategies, with particular attention to variations of gradient descent such as momentum-based methods, stochastic gradient descent (SGD), and adaptive algorithms. These works collectively highlight the continuous effort to accelerate training convergence and enhance model robustness—areas central to the tuning of learning rate and momentum in neural network training.

The third group comprises research applying Backpropagation Neural Networks (BPNNs) to medical and economic domains, with an added emphasis on improving predictive performance. This includes efforts to regulate overfitting, conduct sensitivity analysis, and enhance model reliability. The recurring focus on accuracy and stability in this group aligns closely with broader goals in optimizing learning parameters and network design. Overall, the insights from Table 3 demonstrate a multidimensional research landscape, where methodological innovations and domain-specific applications intersect, driving forward both theoretical and practical advancements in neural network optimization.

1. Techniques and Applications of Classification using Neural Network Models

Image-based classification techniques, particularly those using Convolutional Neural Networks (CNNs), have driven great progress in image recognition across a wide range of applications. CNNs are designed to process data with a grid topology, which makes them particularly suitable for image data. CNNs have the ability to automatically extract hierarchical features from images, thus improving classification accuracy [20]. For example, in the field of medical imaging, CNNs have achieved high accuracy rates, such as 99.22% in fracture classification [21]. Optimization techniques such as hyper-parameter adjustment, advanced architectures such as ResNet-152 and Vision Transformers (ViT), and noise reduction have shown superior results in complex environments, with accuracy reaching 99.62% in malware classification [22]. The applications of CNNs cover a wide range of fields, including medical diagnostics, malware detection, and general image categorization [23].

Recent research reveals the applicability of BPNNs in more specific image classification tasks. In medical imaging, twin neural network models were used to classify cardiac ultrasound images of atrial fibrillation patients, with the result of improved accuracy of structural parameters [24]. In neonatal care, a deep learning system with a combination of Inception-v3 CNN and LSTM layers achieved 85% accuracy in classifying neonatal manipulation and associated physiological changes [25]. In histopathology, ensemble residual networks with iterative random hyper-parameter optimization achieved 98.7% accuracy in colorectal cancer classification for nine tissue classes [26]. However, there are challenges in the classification of images from different sources, such as bovine blastocyst images, where accuracy varies significantly between microscope types [27].

This finding aligns with recent studies demonstrating the effectiveness of CNNs in extracting complex features from image data, enabling high accuracy in applications such as medical diagnosis, malware detection, and histopathological classification. The success of these models is further enhanced by the implementation of advanced architectures such as ResNet and Vision Transformers, as well as optimization techniques like hyper-parameter tuning.

Despite these advancements, both bibliometric trends and empirical findings highlight ongoing challenges, particularly the reliance on large amounts of labeled data and sensitivity to data source variability. For instance, classification accuracy may vary significantly depending on the type of imaging equipment used. These issues underscore the need for more adaptive models capable of robust generalization across diverse data environments. Therefore, future research should focus on developing hybrid models and adaptive algorithms to enhance the practical applicability and reliability of CNN-based classification in real-world settings.

2. Optimization of Learning Processes with Gradient Descent and Momentum

The optimization process in deep learning relies heavily on techniques such as gradient descent and momentum. Gradient descent plays an important role in minimizing the loss function, while momentum improves convergence speed and training stability. Stochastic Gradient Descent (SGD) is widely used due to its low storage requirement and high computational speed, especially in the context of deep learning [28]. To overcome convergence challenges in complex models, a variant of SGD with momentum is used. The standard momentum technique accelerates convergence by considering past gradients, while Windowed Momentum enhances it by using a fixed weight update history, resulting in an average 32% speedup in convergence time. In federated learning environments, adaptive momentum-based methods such as AdaMFCGD reduce sample and communication complexity, demonstrating efficiency in distributed optimization tasks [29]. Gradients have a major role in steering the optimization process by indicating the direction to adjust weights, which is essential for effective learning in neural networks.

Recent research developed additional optimization techniques that improve the efficiency of deep learning training. Ando & Takefuji [10] proposed a random hyper-parameter setting method for the Adam optimizer, which accelerates training on binary tree-shaped LSTMs. A hashing-based technique to reduce computational cost on neural networks without compromising accuracy, making it suitable for parallel training [31]. Liu et al. [32] developed the SBAG algorithm that combines stochastic block coordinate descent with adaptive

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learning rate, showing better training speed and generalization ability on complex DNNs. In addition, although not directly related to optimization techniques, Ekayanti et al. [33] examined the use of a discovery learning model to improve critical thinking skills in physics education, specifically on momentum and impulse phenomena.

Optimization techniques such as gradient descent and momentum are core components in efficient neural network training. Gradient descent, particularly its variants such as Stochastic Gradient Descent (SGD), provides a fast and resource-efficient strategy to minimize the loss function, while momentum helps address the issue of slow convergence by incorporating the trajectory of previous gradients. The integration of advanced methods such as Windowed Momentum and adaptive algorithms like AdaMFCGD represents significant progress in enhancing training efficiency, both in conventional and federated learning environments. Moreover, novel techniques such as the SBAG algorithm and hashing-based optimization approaches further broaden the applicability of neural network training by offering improved scalability and performance, particularly in handling complex and high-dimensional models.

From a practical standpoint, these optimization advancements contribute to more stable and faster model convergence, enabling researchers and practitioners to train deep learning models more effectively with limited computational resources. This is particularly relevant in real-world applications involving large-scale or distributed datasets, such as medical diagnostics, financial forecasting, or remote sensing, where efficient and adaptive training processes are crucial. The continuous refinement of these techniques can significantly lower the barriers to implementing deep learning solutions in industry settings, especially in scenarios where computational efficiency, adaptability, and model robustness are critical success factors.

3. Prediction Models and Artificial Neural Network Analysis

BPNN is a powerful predictive tool in areas such as energy consumption, economic forecasting, and finance. Their ability to model complex and non-linear relationships makes them effective for various prediction tasks [34]. ANN structures such as multilayer perceptrons and Elman networks have demonstrated the ability to reduce errors in certain forecasting tasks [35]. However, challenges such as error analysis and model stability remain important concerns. Errors in deep learning can be divided into approximation, generalization, and optimization errors, all of which affect convergence speed and model performance, especially in the face of the curse of dimensionality [36]. To improve stability and accuracy, techniques such as regularization, hyper-parameter setting, and ensemble methods are used to reduce overfitting and increase model robustness [37]. In addition, the integration of ANNs with other machine learning methods further strengthens the predictive performance.

In the medical field, BPNNs and machine learning algorithms have shown potential in predicting treatment outcomes and improving model accuracy. For example, BPNN models achieved high accuracy in predicting patient response to combination therapy for chronic hepatitis C using baseline data [38]. In diabetic macular edema patients treated with ranibizumab, BPNN showed good correlation in predicting visual outcomes [8]. Moreover, machine learning algorithms such as regularized logistic regression outperformed traditional clinical trials in predicting the effectiveness of spinal cord stimulation for chronic pain management [39]. To handle high-dimensional data, sequential sensitivity analysis and randomized training approaches have been proposed to reduce validation time and improve accuracy [15]. This research demonstrates the potential of BPNN and machine learning in supporting treatment decisions and improving prediction models in various medical applications.

Research on BPNNs shows that this technology is highly effective in predicting outcomes based on complex data. ANN structures such as multilayer perceptrons and Elman networks offer flexible approaches for specific forecasting tasks, but error analysis is an important aspect to improve model accuracy and stability. Approaches such as regularization and ensemble methods help address the problem of overfitting, while integration with other machine learning algorithms shows potential to further improve model performance. In the medical field, BPNNs not only predict outcomes with high accuracy but also support clinical decision-making, such as in the treatment of chronic hepatitis C and diabetic macular edema. However, challenges such as high dimensionality of data require optimization strategies such as sequential sensitivity analysis to maintain efficiency and accuracy.

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Research on BPNN reveals the effectiveness of this technology in modeling complex and non-linear relationships for prediction tasks, both in the economic and medical sectors. Network structures such as multilayer perceptrons and Elman networks offer solutions to various forecasting challenges. However, in-depth error analysis remains a critical component in improving model performance. Optimization techniques such as regularization and ensemble methods have shown significant improvements in stability and accuracy. The integration of BPNN with other machine learning algorithms further extends its ability to handle high-dimensional data and other complex situations.

This synthesis across clusters underscores that advances in ANN-based prediction models are not solely driven by architectural innovations, but also by continuous refinement of training dynamics through hyper-parameter optimization. The recurring focus on learning rate, momentum, and stability techniques across varied domains ranging from image classification to economic forecasting demonstrates a shared methodological core. As such, integrating insights from diverse applications enables a more comprehensive understanding of how parameter tuning strategies can be generalized, adapted, and improved to enhance ANN performance in increasingly complex problem spaces.

CONCLUSION

Based on the analysis, this study highlights that combining momentum-based learning with adaptive learning rate adjustment significantly accelerates convergence and improves the accuracy of backpropagation neural networks (BPNN). The integration of these optimization techniques reduces prediction errors and enhances model stability across applications. In medicine, BPNN effectively predicts treatment outcomes, enabling data-driven decision-making with high precision. In economics and finance, BPNN models complex non-linear relationships, improving forecasting accuracy. However, challenges such as the curse of dimensionality, overfitting, and large dataset requirements persist. Techniques like regularization, ensemble methods, and sensitivity analysis demonstrate potential to address these issues. Future research should focus on developing hybrid optimization algorithms and exploring multidisciplinary collaborations to further improve BPNN performance and broaden its practical applications.

The results of this study carry important implications for both academic research and practical applications involving neural network optimization. The demonstrated benefits of combining momentum-based learning with adaptive learning rate adjustment indicate that well-designed hyper-parameter strategies can lead to more accurate, stable, and efficient BPNN models. These findings are particularly relevant for high-stakes domains such as healthcare, finance, and energy forecasting. Moving forward, future research should focus on developing hybrid optimization algorithms that integrate metaheuristic techniques with backpropagation to address persistent challenges such as overfitting and slow convergence. In addition, incorporating explainable AI methods will enhance model transparency and trust, especially in sensitive applications. Expanding interdisciplinary collaboration is also essential to ensure that optimization strategies are robust, generalizable, and aligned with real-world problem contexts.

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