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MOBILENET PERFORMANCE IMPROVEMENTS FOR DEEPFAKE IMAGE IDENTIFICATION USING ACTIVATION FUNCTION AND REGULARIZATION

Handrie Noprisson[1*]; Vina Ayumi[2]; Mariana Purba [3]; Nur Ani[4]

Department of Informatics Engineering[1,2]
Universitas Dian Nusantara, Indonesia[1,2]
https://undira.ac.id/[1,2]
handrie.noprisson@dosen.undira.ac.id[1*], vina.ayumi@dosen.undira.cid[2]

Department of Informatics[3]
Universitas Sjakhyakirti, Indonesia[3]
https://unisti.ac.id[3]
mariana_purba@unisti.ac.id[3]

Institute of Visual Informatics[4]
Universiti Kebangsaan Malaysia[4]
https://www.ukm.my/portalukm[4]
p93828@siswa.ukm.edu.my[4]

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

Abstract— *Deepfake images are often used to spread false information, manipulate public opinion, and harm individuals by creating fake content, making developing deepfake detection technology essential to mitigate these potential dangers. This study utilized the MobileNet architecture by applying regularization and activation function methods to improve detection accuracy. ReLU (Rectified Linear Unit) enhances the model's efficiency and ability to capture non-linear features, while Dropout and L2 regularization help reduce overfitting by penalizing large weights, thereby improving generalization. Based on experimental results, the MobileNet model optimized with ReLU and Dropout achieved an accuracy of 99.17% in the training phase, 85.34% in validation, and 70.60% in testing, whereas the MobileNet model optimized with ReLU and L2 showed lower accuracy in the training and validation phases compared to Dropout but achieved higher accuracy in testing at 72.18%. This study recommends MobileNet with ReLU and L2 due to its better generalization ability when testing data (resulting from reduced overfitting).*

Keywords: *activation function, deepfake, regularization, transfer learning.*

Intisari— *Citra deepfake sering digunakan untuk penyebaran informasi palsu, manipulasi opini publik, dan membahayakan individu melalui pembuatan konten palsu, sehingga teknologi deteksi citra deepfake penting dikembangkan untuk mengurangi potensi bahaya tersebut. Penelitian ini menggunakan arsitektur MobileNet dengan melakukan penerapan regularization dan metode activation function meningkatkan akurasi deteksi. ReLU (Rectified Linear Unit) meningkatkan efisiensi dan kemampuan model dalam menangkap fitur non-linear, sementara Dropout dan L2 regularization membantu mengurangi overfitting dengan memberikan penalti pada bobot yang besar sehingga meningkatkan generalisasi. Berdasarkan hasil eksperimen, model MobileNet yang dioptimasi dengan ReLU dan Dropout mendapatkan akurasi pada tahap pelatihan sebesar 99.17%, tahap validasi sebesar 85.34% dan tahap pengujian sebesar 70.60% sedangkan model MobileNet yang dioptimasi dengan ReLU dan L2, akurasi menurun pada tahap pelatihan dan tahap validasi jika dibandingkan dengan regularisasi Dropout, namun meningkat pada tahap pengujian sebesar 72.18%. Penelitian ini merekomendasikan MobileNet dengan ReLU dan L2 karena kemampuan generalisasi yang lebih baik pada data pengujian (akibat pengurangan overfitting).*

Kata Kunci: *fungsi aktivasi, deepfake, regularisasi, pembelajaran transfer.*

INTRODUCTION

One of the problems in the modern digital world is the rapid development and spread of false information through social media platforms, enabled by the automated manipulation of images and videos using a deep learning-based approach called deepfakes [1], [2]. Deep learning techniques were applied to perform successive operations to extract intrinsic information from the data to be manipulated. Deepfake content was made famous on social media for its ability to stimulate imagination by creating surreal and fantastical events, such as presenting David Beckham speaking several languages and others. However, the potential negative impacts were also highlighted as a concern by many researchers worldwide, leading to efforts to detect deepfake content effectively using various approaches. This research was conducted to improve the performance of MobileNet, which had been previously used for deepfake image detection [3]–[5].

Deepfake images, manipulated images, or videos created using artificial intelligence were recognized as a significant threat to society. Deepfake imagery was used to spread false information, manipulate public opinion, and harm individuals by creating false content, making detecting deepfake imagery essential to protect against these potential dangers [6]–[10]. Transfer learning approaches were applied in several previous studies to detect and classify deepfake images. A ResNet-18 approach combined with a quantum neural network layer was proposed by Mishra and Samanta to classify deepfake images [11]. Suratkar and Kazi also proposed a new framework that utilized transfer learning in autoencoder convolutional neural networks (CNNs) to detect deepfakes, achieving good generalization and effective results [12].

Previous studies, such as those by Mishra and Samanta, focused on combining ResNet-18 with quantum neural networks for deepfake image classification [11]. At the same time, Suratkar and Kazi utilized transfer learning in autoencoder CNNs to detect deepfakes, achieving promising results [12]. However, a gap was identified in balancing efficiency and performance due to the reliance on computationally expensive architectures like ResNet-18. This gap was addressed in this study by proposing the use of MobileNet. This lightweight yet effective model reduced the number of parameters, computational costs, and the risk of overfitting while maintaining good accuracy. MobileNet was further optimized to detect deepfakes generated by various technologies, providing a practical solution for real-world applications requiring fast and accurate detection.

Regularization mechanisms that combined multiple detection methods were proposed and were found to enhance detection accuracy further. Optimizations for MobileNet were also suggested in artificial intelligence to improve its real-time performance and resource utilization, making it more efficient for deepfake detection [13]–[15]. However, the role of regularization and activation functions on MobileNet had yet to be explored, leaving room for further enhancements in classification performance on deepfake datasets. Improvements in deepfake detection were obtained from previous research by leveraging the MobileNet architecture, which was optimized for maintaining high accuracy while reducing the number of parameters, computation time, and overfitting [16], [17].

The novelty of this research was demonstrated by investigating the combined effects of regularization and activation functions on the MobileNet architecture. This area had yet to be thoroughly explored in previous studies [17]–[21]. While earlier research focused on optimizing MobileNet for real-time performance, resource utilization, and overall efficiency, this study specifically evaluated the impact of ReLU activation with Dropout (experiment 1) and ReLU activation with L2 regularization (experiment 2) on classification performance for deepfake datasets. The study aimed to identify the most effective combination for improving accuracy and reducing overfitting by analyzing these configurations. This approach introduced a new perspective on optimizing MobileNet for high-accuracy deepfake detection, addressing gaps in existing literature and contributing to advancements in the field.

MATERIALS AND METHODS

This research was conducted through a series of steps, beginning with a literature study to understand existing deepfake detection techniques, followed by dataset preparation to ensure sufficient and relevant data for training and testing the models. Two experiments were carried out, including experiment 1, which utilized MobileNet with ReLU and Dropout to enhance feature extraction while reducing overfitting, and experiment 2, which employed MobileNet with ReLU and L2 regularization for improved generalization. Finally, the models were evaluated to compare their accuracy and effectiveness in detecting deepfake images, providing insights into

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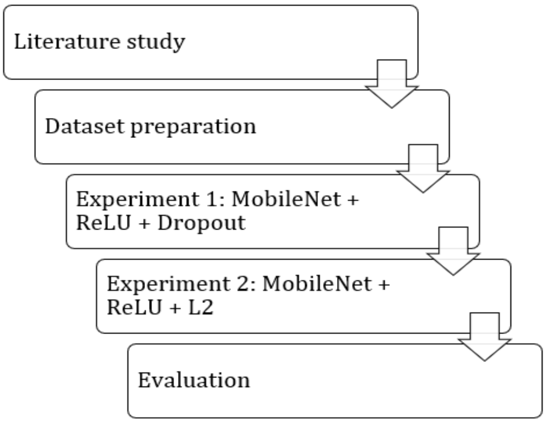
their performance. The research stage can be seen in **Figure 1.**



Source: (Research Results, 2024)
Figure 1. Research methodology

The first stage involved the development of a deepfake image dataset collected from DF-Platter [22] , Celeb-DF [22] and Google Images. The dataset was categorized into "fake images" and "real images." It was divided into three parts: training, validation, and testing. In the training dataset, 70,000 images were labeled as fake and 70,000 as real, allowing the model to learn the distinctions between manipulated and authentic images. The compilation of datasets from DF-Platter, Celeb-DF, and Google Images is illustrated in **Figure 2.**

Source: (Research Results, 2024)

Figure 2. Dataset compilation from DF-Platter, Celeb-DF and Google Images

In image processing theory, real images were described as having consistent lighting, shadows, and facial textures that adhered to natural physical laws, with fine details such as pores and hair appearing clearly. Conversely, deepfake images exhibited inconsistencies in lighting, blurry textures, and artifacts in specific areas, particularly along facial edges. A frequency analysis of deepfake images was conducted, and unnatural noise patterns or distortions from the synthesis process were revealed.

The dataset for the validation stage was composed of 19,600 images for the fake images class and 19,600 images for the real images class, which were used to evaluate the model's performance during the training process. The dataset for the testing phase was prepared with 5,492 images for the fake images class and 5,413 images for the real class, which were used to measure the accuracy and effectiveness of the MobileNet model after the completed training process.

The first detection experiment was conducted using the MobileNet architecture combined with ReLU and Dropout, called MobileReLuDr, to improve the model's performance in detecting deepfake images. Each component was assigned a vital role in improving generalization and preventing overfitting. The dropout rate was set to 0.2, as defined in model.add(Dropout(0.2)), to mitigate overfitting. The learning rate was configured at 0.0001 using the Adam optimizer for stable and gradual updates. The training was performed with a batch size of 32 over 50 epochs, as specified in the generator and fit functions.

The second detection experiment was conducted using the MobileNet architecture combined with ReLU and L2 Regularization, referred to as MobileReLuL2. The strength was set to 0.02 and was applied to the Dense layers using regularizers.L2(l2=0.02). A learning rate of 0.0001 was configured with the Adam optimizer, and training was performed with a batch size of 32 over 50 epochs. Weight initialization was leveraged from pre-trained MobileNet weights on imaginet to enhance feature extraction in the early layers.

The configuration parameters of the MobileNet model were defined with the first layer as an input layer producing outputs of shape (100, 256, 256, 3). The architecture employed a MobileNet backbone pre-trained on ImageNet, followed by a GlobalAveragePooling2D layer to reduce dimensionality while retaining spatial features. The classification head was constructed with a Dense layer containing 4096 units and ReLU activation, another with 1072 units and ReLU

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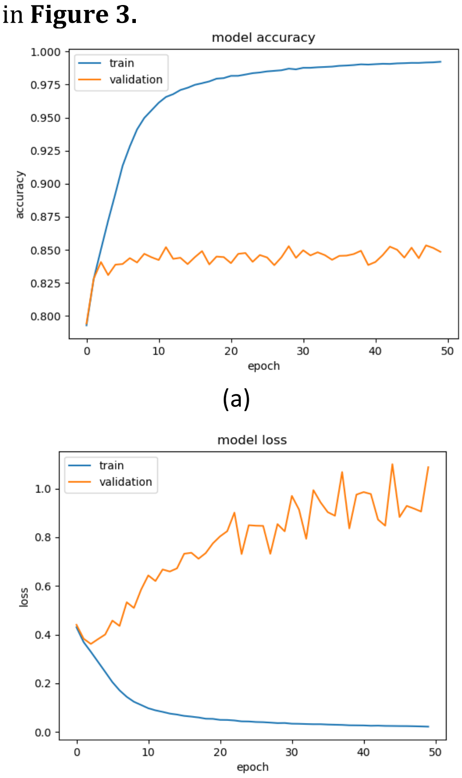
activation, and a final Dense layer with two units using softmax activation for binary classification. These layers were designed to classify input images as deepfake or non-deepfake, leveraging robust feature extraction and regularization to mitigate overfitting.

RESULTS AND DISCUSSION

The first experiment, MobileReLuDr, utilized the MobileNet architecture with ReLU and Dropout to enhance deepfake image detection by improving generalization and preventing overfitting. A dropout rate of 0.2 and a learning rate of 0.0001 with the Adam optimizer ensure stability during training. The model is trained with a batch size of 32 over 50 epochs to achieve optimal performance. The result of accuracy and loss for each epoch on the MobileNet with ReLU and Dropout model can be seen in **Figure 3.**

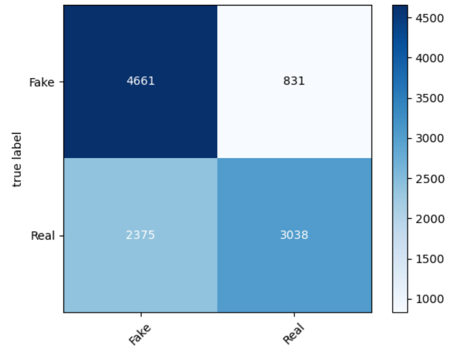


(a)

(b)

Source: (Research Results, 2024)
Figure 3. Result of accuracy (a) and loss (b) of MobileReLuDr

The MobileReLuDr model performance on deepfake datasets was evaluated using the confusion matrix, providing insights into accurate and incorrect predictions as many 4661 true positives (fake detected as fake) and 3038 true negatives (real detected as real) were shown. Additionally, 2375 false positives (real misclassified as fake) and 831 false negatives (fake misclassified as real) were observed. The results of confusion matrix from experiments using MobileReLuDr can be seen in **Figure 4.**



Source: (Research Results, 2024)
Figure 4. Confusion Matrix of MobileReLuDr

Based on the values in the confusion matrix, other classification evaluation values such as accuracy, precision, recall, F1-score can be calculated. The testing phase using MobileReLuDr model using deepfake image datasets will be analyzed using precision, recall, F1-score values. The precision, recall, F1-score values of the MobileReLuDr experiment can be seen in **Table 1.**

Table 1. Precision, recall and f1-score of MobileReLuDr

Data	Precision	Recall	F1-Score	Support
Fake	0.66	0.85	0.74	5492
Real	0.79	0.56	0.65	5413
Accuracy			0.71	10905
Avg.	0.72	0.71	0.70	10905

Source: (Research Results, 2024)

Based on the experimental results, the MobileReLuDr model was found to have a precision of 66% for fake images class, meaning 66% of images predicted as "fake" were actually fake, while a higher accuracy of 79% was achieved for the "real images" class. The F1-score for the "fake images" class was calculated as 0.74, showing a good balance between precision and recall, whereas the F1-score for the "real images" class was determined to be 0.65, highlighting areas for improvement in detecting authentic images.

In the second experiment, MobileReLuL2 was used, combining the MobileNet architecture with ReLU and L2 Regularization, where the L2 strength was set to 0.02 for Dense layers. The model was trained with a learning rate of 0.0001 using the Adam optimizer, a batch size of 32, and pretrained weights from "imagenet" for feature extraction. Training and validation were conducted on a deepfake image dataset, with epochs adjusted according to the dataset size, and the results were

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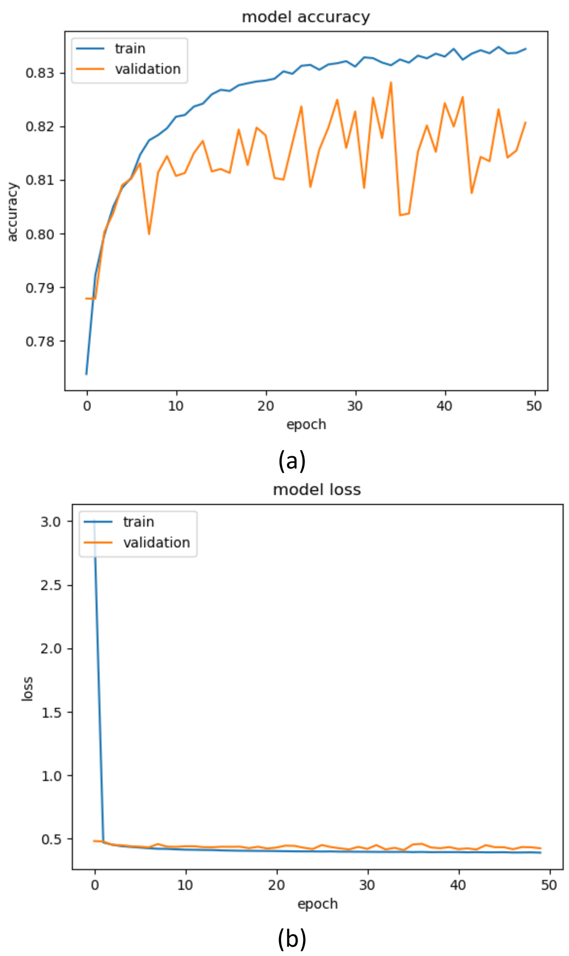
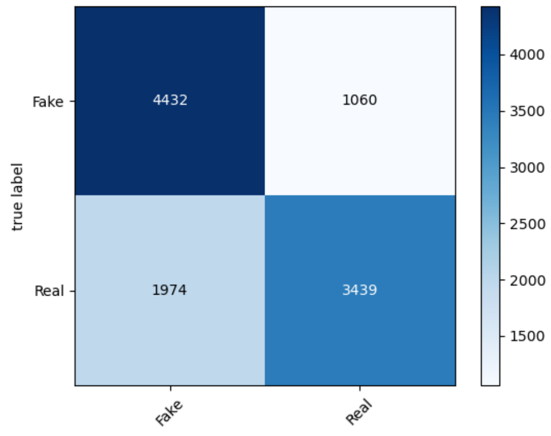
presented graphically. The MobileReLuL2 model was found to fit well during testing and validation, as shown by the accuracy and loss trends depicted in **Figure 5**.



Source: (Research Results, 2024)
Figure 5. Result of accuracy (a) and loss (b) of MobileReLuL2

The confusion matrix for the MobileNet model with ReLU and L2 regularization was analyzed to evaluate the correct and incorrect classifications of deepfake datasets. It was shown that 4432 fake images were correctly classified as fake (true positives) and 3439 real images were correctly classified as real (true negatives). however, 1974 real images were misclassified as fake (false positives), and 1060 fake images were misclassified as real (false negatives). The confusion matrix was used to provide accurate and predictive information regarding the classification performance of the model, with its sections representing the numbers of true and false predictions for each deepfake dataset class. The results from the experiments using MobileReLuL2 were depicted in **Figure 6**.



Source: (Research Results, 2024)
Figure 6. Confusion matrix of MobileReLuL2

Based on the values in the confusion matrix, other classification evaluation values such as accuracy, precision, recall, F1-score can be calculated. The testing phase using the MobileNet with reLU and L2 model using deepfake image datasets will be analyzed using precision, recall, F1-score. The precision, recall, f1-score values of the MobileNet with reLU and L2 experiment can be seen in **Table 2.**

Table 2. Precision, recall and f1-score of MobileNet with reLU and L2

Data	Precision	Recall	F1-Score	Support
Fake	0.69	0.81	0.74	5492
Real	0.76	0.64	0.69	5413
Accuracy			0.72	10905
Avg	0.73	0.72	0.72	10905

Source: (Research Results, 2024)

The performance of the MobileReLuL2 model for deepfake detection was evaluated, and it was found to perform well in detecting fake images with high recall and precision. Although the "fake images" class showed good results, shortcomings were observed in detecting real images, as reflected in the lower recall and F1-score for the "real images" class. Improvements were identified as necessary for native image recognition to reduce the risk of misclassification. It was suggested that future efforts focus on data augmentation techniques, hyperparameter tuning, and exploring more complex model architectures to enhance the model's performance.

The precision for the "fake images" class was recorded at 69%, indicating that 69% of images predicted as fake were actually fake, and the model effectively avoided false positives in this category. The accuracy for the "real images" class was noted

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as 76%, demonstrating that the model was more accurate in identifying authentic images. High precision in both classes was recognized as critical for deepfake detection to minimize the likelihood of misclassifying real images as fake.

The recall for the "fake images" class was found to be 81%, indicating that 81% of fake images in the dataset were correctly identified, demonstrating the model's effectiveness in detecting manipulated content. However, the recall for the "real images" class was lower, at 64%, suggesting that many original images were not correctly identified, resulting in an increased number of false negatives. The F1-score for the "fake images" class was 0.74, highlighting a good balance between precision and recall, while the F1-score for the "real images" class was lower at 0.69.

The performance of the MobileReLuDr and MobileReLuL2 models on deepfake datasets was compared using their respective confusion matrices, providing insights into accurate and incorrect predictions. For MobileReLuDr, it was observed that 4661 fake images were correctly classified as fake (true positives), while 3038 real images were correctly classified as real (true negatives). However, 2375 real images were misclassified as fake (false positives), and 831 fake images were misclassified as real (false negatives). These results highlighted that the model achieved strong performance in detecting fake images but struggled with reducing false positives.

In contrast, the MobileReLuL2 model showed that 4432 fake images were correctly classified as fake (true positives) and 3439 real images were correctly classified as real (true negatives). However, 1974 real images were misclassified as fake (false positives), and 1060 fake images were misclassified as real (false negatives). Compared to MobileReLuDr, the MobileReLuL2 model exhibited slightly lower performance in detecting fake images but showed an improvement in reducing false positives, resulting in more accurate classification of real images. The comparison results of the experiment from this research can be seen in **Table 3.**

Table 3. Comparation of experiment result

Model	Train	Val	Test
MobileReLuDr	99.17%	85.34%	70.60%
MobileReLuL2	83.13%	82.81%	72.18%

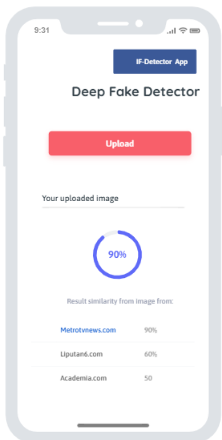
Source: (Research Results, 2024)

MobileNet models optimized with ReLU and dropout get accuracy at the training stage of 99.17%, validation stage of 85.34% and testing stage of 70.60%. In MobileNet models optimized with ReLU and L2, accuracy decreased in the training and validation phases, but increased in the testing phase by 72.18%.

From the comparison of the given models, we can see the performance of each model based on accuracy metrics on three data sets: Train, Validation (Val), and Test. The MobileReLuDr model showed high accuracy on the training data (99.17%), which showed that the model could learn the patterns in the training data very well. However, the accuracy of the validation data (85.34%) and test data (70.60%) showed a significant decrease. MobileReLuDr is likely to be overfitted, where the model fits the training data well but needs to generalize better to the new deepfake image data. Dropout is a regulatory technique used to prevent overfitting, but it does notisn't effective enough in this case.

The MobileReLuL2 model has lower accuracy on the training data (83.13%) than the MobileReLuDr model. These results may indicate that MobileReLuL2 does not fully capture patterns in the training data but could lead to more generalized models. The accuracy of MobileReLuL2 on validation data (82.81%) and test data (72.18%) is closer to the accuracy of training, indicating that MobileReLuL2 is better at generalizing patterns to new data compared to the MobileReLuDr model.

The best model is the MobileReLuL2 model. The next step is implementing the MobileReLuL2 model file in *.h5 format in the image deepfake detector (IF-Detector) application. The MobileReLuL2 model is integrated into the application to detect deepfakes using Keras. The interface design of the IF-Detector application is seen in **Figure 7.**



Source: (Research Results, 2024)

Figure 7. Interface of IF-Detector application

In developing an image deepfake detector (IF-Detector) application based on the .h5 model, Python, TensorFlow and several other supporting libraries, such as OpenCV, are needed to handle

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images. The data is fed into the deepfake detector model in the image box. The data in the image format must conform to the model input specifications.

MobileReLuL2 can process image inputs in the form of numerical arrays. After input processing, the image is fed into the MobileReLuL2 model to make predictions. The next step is to integrate MobileReLuL2 into a .h5 model-based image deepfake detector (IF-Detector) application using the programming code seen in **Figure 8**.

```
def load_image():
    file_loc = filedialog.askopenfilename()
    if file_loc:
        messagebox.showinfo("Result",
        "Your image is deepfake image!"
        if is_deepfake(file_loc) else
        "This is real image.")

def deepfake_detection(file_loc):
    capture = cv2.imread(file_loc)
    input = np.expand_dims(cap, axis=0)
    h5_prediction = model.predict(frame_input)
    return h5_prediction[0][0] > 0.5

root = tk.Tk()
tk.Button(root, text="upload image",
            command=load_image).pack()
root.mainloop()
```

Source: (Research Results, 2024)

Figure 8. Implementation of *h5 into IF-Detector application

CONCLUSION

The study was conducted to contribute to the field of deepfake detection by demonstrating the effectiveness of the MobileNet architecture combined with distinct regularization techniques and activation functions, specifically through the MobileReLuDr and MobileReLuL2 configurations. The MobileReLuDr model, which utilized ReLU activation and a Dropout rate of 0.2, was shown to effectively mitigate overfitting while maintaining stability during training with a learning rate of 0.0001. In contrast, the MobileReLuL2 model was designed with ReLU activation and L2 Regularization with a strength of 0.02, and pre-trained weights were leveraged to enhance feature extraction, resulting in better generalization during testing.

The research findings were highlighted by the varying performances of MobileNet models optimized with different regularization and activation function methods in deepfake image classification. MobileReLuL2 was found to outperform MobileReLuDr in the testing phase, achieving an accuracy of 72.18% compared to 70.60%, which indicated better generalization to unseen data. MobileReLuDr, however, was observed to exhibit higher accuracy in the training (99.17%) and validation stages (85.34%) due to its stronger performance during early stages of learning. The MobileNet architecture was successfully utilized to maintain a good balance between accuracy, computational efficiency, and reduced overfitting by incorporating regularization techniques.

While this study successfully developed and utilized a deepfake image dataset compiled from DF-Platter, Celeb-DF, and Google Images, several limitations should be acknowledged. First, the dataset size, while extensive for training, may not fully represent the diversity of deepfake media, particularly across different formats, such as videos or lesser-studied deepfake techniques. Additionally, overfitting issues, although mitigated using Dropout and L2 Regularization, may still affect the generalizability of the models to unseen datasets or more complex manipulation techniques. Future research could focus on expanding the dataset to include other types of deepfake media, such as videos, and experimenting with additional regularization techniques, such as mixup or adversarial training, to further reduce overfitting. Model enhancements, such as integrating attention mechanisms or hybrid architectures, could also be explored to improve the detection of subtle manipulations in deepfake content.

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