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Deep Learning Based Face Mask Detection System Using MobileNetV2 for Enhanced Health Protocol Compliance

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Abstract

Personal protective equipment (PPE) is crucial in mitigating the spread of infections within the pharmacy industry, manufacturing sectors, and healthcare facilities. Airborne particles and contaminants can be released during the handling of pharmaceuticals, the operation of machinery, or patient care activities. These particles can be transmitted through close contact with an infected individual or by touching contaminated surfaces and then touching one's face (mouth, nose, or eyes). PPE, including face masks, plays a vital role in minimizing the risk of transmission of infectious diseases. Although mandates for wearing face masks might relax as situations improve and vaccination rates increase, staying prepared for potential future outbreaks and the resurgence of infectious diseases remains important. Therefore, an automated system for face mask detection is important for future use. This research proposes real-time face mask detection by identifying who is (i) not wearing a mask and (ii) wearing a mask. This research presents a deep-learning approach using a pre-trained model, MobileNet-V2. The model is trained on a 10,000 dataset of images of individuals with and without masks. The result shows that the pre-trained MobileNet-V2 model obtained a high accuracy of 98.69% on the testing dataset.

Keywords: Face Mask Detection, Personal Protective Equipment (PPE), Convolutional Neural Network (CNN), Process Innovation

1. Introduction

Face masks in pharmacies, manufacturing, and healthcare facilities have become critical in maintaining workplace safety and public health [1]. In these settings, face masks are a primary defense against inhaling harmful airborne particles, including pathogens, chemicals, and other irritants that can compromise respiratory health. Especially in the wake of global health crises, these industries have recognized the indispensable role of protective masks in preventing disease transmission and ensuring a safe working environment [2].

In the pharmacy industry, pharmacists and staff constantly interact with the public, including patients who may be immunocompromised or carrying infectious diseases [3]. The enclosed spaces of pharmacies compound the risk of airborne transmission. By wearing masks, pharmacy workers can significantly reduce the spread of respiratory droplets expelled when talking, coughing, or sneezing. Moreover, masks help protect the staff from exposure to medication particles or other allergens in pharmacy environments, ensuring worker and patient safety.

Similarly, face masks are vital in manufacturing settings, especially those involving the production of pharmaceuticals, chemicals, or food products [4]. They not only prevent product contamination but also protect workers from inhaling hazardous substances that could lead to occupational diseases. Stringent health and safety regulations in these industries often mandate using specific types of masks, such as N95 respirators, which offer protection against particulate matter.

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Compliance with these regulations is closely monitored to maintain high safety standards and prevent workplace-related illnesses. Healthcare facilities, perhaps the most critical areas for mask usage, require strict adherence to mask protocols to protect healthcare providers and patients from infectious diseases [5]. In hospitals, clinics, and care homes, masks are essential for creating barriers against transmitting infectious agents, particularly in high-risk areas such as emergency rooms, intensive care units, and during surgical procedures.

The sustained use of face masks in the pharmacy industry, manufacturing, and healthcare facilities is a proven strategy to mitigate health risks associated with airborne particles [6]. As these industries evolve with health and safety advancements, integrating mask-wearing protocols remains a cornerstone of occupational health and safety practices.

To ensure compliance with face mask mandates, machine learning techniques have been employed to develop automated face mask detection systems [7]. These systems utilize cameras and image processing algorithms to identify whether individuals wear face masks [8], [9].

The significance of developing face mask detection is that it is significant in controlling the spread of the virus by ensuring compliance with mask-wearing guidelines in certain places where we are required to wear masks, such as healthcare facilities and public transportation. It promotes greater adherence to mask-wearing guidelines, as people may forget to wear masks, increasing the transmission risk. Individuals not wearing masks can receive feedback and be reminded to take the necessary precautions to protect themselves and others. Next, face mask detection can reduce the burden on human resources required to monitor everyone. Additionally, it saves a tonne of time, making monitoring, especially in public locations, beneficial for the concerned authority to enforce strict regulations and responsibility to stop the infection from spreading.

Recent studies have highlighted the effectiveness of these systems in various settings, including healthcare facilities and public transportation, where monitoring mask usage is crucial [8], [9]. For instance, a strategic review published in 2022 discusses the essential requirements and performance of different machine-learning models used for face mask detection[8]. Another survey from 2023 provides a comprehensive analysis of deep learning techniques applied to this problem, emphasizing the importance of object detection in ensuring public health safety [9]. Automated detection systems can significantly aid in maintaining compliance and reducing the spread of the virus.

2. Face Mask Detection Based on Deep Learning Approach

Public health has highlighted the need for effective face mask detection to ensure public health safety [10]. Deep learning, a powerful subset of machine learning, has been successfully applied to develop automated face mask detection systems. These systems use convolutional neural networks (CNNs) to analyze images and determine whether individuals wear masks correctly. Recent advancements have created highly accurate and efficient models like MobileNetV2, ResNet50, and VGG16. These models are trained on extensive datasets, enabling them to detect mask usage reliably in real time. Implementing these systems can significantly enhance compliance with mask mandates, reducing the burden on human resources and improving public health monitoring.

2.1. Face Mask

A face mask is a covering used to cover part of the face. People wear face masks for a variety of reasons. Some do so for aesthetic reasons, while others do so to protect themselves from pollution, weather, health issues, etc. The use of face masks protects against airborne contaminants like pollen, chemical fumes, and pathogens [11].

Since the Middle Ages, when doctors wore beak-shaped masks to protect themselves from the plague's miasma, face masks have been used. However, no proof exists that the " beak-shaped masks" existed [12]. Figure 1 depicts the evolution of face masks from the beak-shaped mask of the 1800s (A) to the bulky industrial masks of the 1900s (B), which evolved into surgical masks (C). The government has recommended face covers made of any available cloth (D) material because of the limited resources of face masks [13].

Figure 1. Evolution of Face Masks [13].

2.2. Deep Learning

A subset of machine learning known as deep learning (DL) includes training artificial neural networks to carry out various tasks. It mimics the learning process of the human brain. DL can improve the outcome through repetition without human intervention. DL has become one of the most well-known research trends. Deep learning algorithms have become increasingly popular because of the huge amount of data from several sources, including social media, the internet, search engines, and e-commerce platforms. This data is often unstructured, making it challenging and time-consuming for humans to extract meaningful features.

Unlike conventional machine learning methods, DL possesses the unique capability to learn feature sets for multiple tasks. Deep learning automatically facilitates both learning and classification in a single step, streamlining the overall process [14]. DL models consist of multiple neural layers, starting with the initial layer and progressing through the subsequent layers to increase the level of abstraction [15].

2.3. Convolutional Neural Network

Convolutional Neural Networks (CNN) are among the most popular due to their excellent performance in image-based machine-learning problems. CNN has several layers, including the convolutional, pooling, and fully connected layers, where the convolutional and fully connected layers have parameters [16].

The convolutional layer, which contains a collection of filters whose parameters must be learned during training, is the main component of CNN [17]. Most of the dominant information is maintained throughout each step of the pooling stage. At the same time, the large size of the input is reduced to create smaller feature maps in the pooling layer to reduce memory usage and simplify the procedure [14]. Max pooling and average pooling are two different types of pooling. While average pooling will take the average value from each map, max pooling will take the maximum value from each feature map. Finally, the CNN architecture typically ends with the fully connected layer following the transformation of the tensor at these layers' output into a vector; several neural network layers were added [18], [19]. This layer's goal is to use the features learned by the preceding layers to make predictions. MobileNet and ResNet are the pre-trained models that were studied in this research.

2.4. MobileNet

The MobileNet concept is designed for mobile apps and hardware with minimal computational power. It is a class of CNN frequently employed in practical applications like object detection. Compared to networks with standard convolutions with the same depth, this approach significantly lowers the parameter count using depth-wise separable convolutions, resulting in more effective and lightweight deep neural networks. Two layers, depth-wise and pointwise convolutions, combine to form a depthwise separable convolution.

A CNN 53 layers deep is called MobileNet-V2 [20], [21]. The primary modifications in the MobileNetV2 architecture involved adopting inverted bottleneck blocks and incorporating residual connections [22], [23]. These changes improved the model's efficiency and performance for mobile and embedded device applications.

Three convolution layers make up MobileNetV2's bottleneck residual block. While MobileNetV1 already includes the last two layers, the MobileNetV2 architecture introduces additional modifications to enhance its efficiency and performance. The first layer of the bottleneck residual block of MobileNetV2 is called the 1x1 expansion layer. Its purpose is to expand the number of channels in data that pass through it.

3. Methodology

The methodology involves preliminary studies, analysis literature review, data acquisition, model development, prototype design, prototype development, and prototype testing and evaluation. As shown in figure 2, the next subtopic will provide a detailed explanation of each phase.

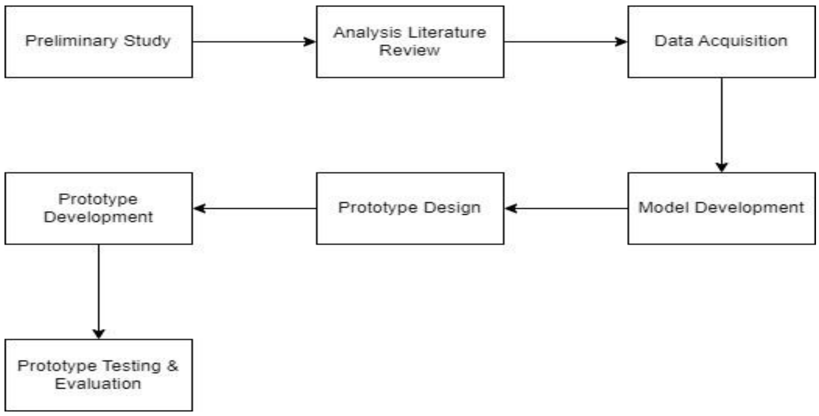

Figure 2. Research Framework

The first objective is to identify the features and differentiate people with and without masks. Phases for achieving this objective include preliminary studies and analysis literature review. The preliminary studies phase aims to identify face mask appearance monitoring problems to ensure public health safety and study the features that differentiate people with and without masks. Next, in the analysis literature review phase, information from previous case studies done on this topic by other researchers has been gathered and analyzed to discover which deep learning technique is most efficient in detecting face masks.

The second objective is to train the CNN algorithm to detect face masks. The phases that have been done to achieve this objective are data acquisition and model development. Images of people with and without masks are gathered during the data acquisition phase. Data pre-processing, model training, and model evaluation occur during the model development phase. Model training includes training the three models using the training dataset and testing the CNN model. In contrast, model evaluation evaluates the model and finds the best model to deploy in real-time detection.

The third objective is to develop a face mask detection prototype using a CNN that can identify the appearance of a face mask on a person. To achieve this objective, prototype design, prototype development, prototype testing, and evaluation have been performed.

The prototype user interface design process was completed during the prototype design phase. Next, in the prototype development phase, the system's encoding process uses Tkinter. Lastly, result testing and documentation are completed in the last phase, prototype testing and evaluation. The prototype is tested using real-time detection and evaluated to ensure it is working as expected.

3.1. Data Acquisition

This phase involved data pre-processing, model training, and model evaluation. In the data pre-processing phase, the acquired images were converted into user-friendly formats, which meant resizing them to 224x224 because the images must be the same size. The technique used during model training was the CNN model, MobileNet-V2.

The input photos, which are the images of people, have been split into training, testing, and validation datasets by the author, then go through data pre-processing to resize the images and label the images. After that, perform data augmentation. The model uses the training dataset, and the CNN architecture model receives the dataset and performs classification. To increase accuracy, the CNN model requires numerous pieces of training with hyperparameter adjustments.

3.2. Prototype Design & Development

A prototype interface is a medium where users interact with the prototype. It is crucial to make the prototype interface user-friendly to ensure that users can use the prototype without difficulty or the need for instruction. This stage involves developing a prototype using Tkinter, which entails creating a fundamental graphical user interface (GUI) to test and verify the essential functionalities of the software application. Tkinter is a widely used Python library for constructing GUI applications, making it a favored option for swift and straightforward prototyping.

The prototype must be evaluated and meet the project objectives before being used by users to meet their expectations. It is important to ensure that the system is accurate and reliable and that input and output are processed correctly. Next, the details will be recorded in documentation so that others can better understand the study and use the system as a reference.

4. Results and Discussion

It outlines the experimental findings from face mask detection models MobileNetV2. The training and validation sets were used for models, and the test set was used to evaluate the model's performance. To evaluate their abilities, they must correctly identify faces with and without masks using a confusion matrix. The experimental results play a critical role in guiding our decision on the most suitable model for face mask detection.

4.1. Experiment MobileNet-V2

In the experiment, the model MobileNet-V2 was evaluated using the Adam optimizer. The architecture consists of one flattened layer, two batch normalization layers, two dropout layers with (0.5), and two dense layers. The batch size used in this experiment is 16. The model was trained up to 30 epochs. Furthermore, two callbacks are used in this architecture, which reduces the learning rate and early stopping.

In the experiment using an architecture with ten epochs, the achieved training accuracy was 0.9792, and the validation accuracy reached 1.000. The corresponding losses were 2.0697 for training and 1.9047 for validation. The training process was completed after epoch 10, and the experiment results were conducted for ten epochs, as shown in table 1.

Table 1. Experiment with 10 Epochs

Epoch	Learning Rate	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1		5.2700	0.9375	5.4323	0.8750
2		4.0311	0.9728	3.2136	1.000
3		2.9683	0.9808	2.5111	1.000
4		2.5997	0.9744	2.5990	1.000
5	0.001	2.8395	0.9631	2.8028	1.000
6		3.0686	0.9583	3.3957	0.9375
7		2.6701	0.9840	2.0797	1.000
8		2.1207	0.9728	2.3614	0.9792

9	2.3767	0.9776	2.4731	0.9167
10	2.0697	0.9792	1.9047	1.000

Figure 3 presents a confusion matrix from an experiment conducted over 10 epochs, illustrating the model's performance in classifying images as either "Mask" or "No Mask." The matrix shows that the model correctly identified 503 cases where individuals were wearing masks (True Positives) and 479 cases where individuals were not wearing masks (True Negatives). However, there were some misclassifications, with 4 instances where the model incorrectly predicted "Mask" when the actual label was "No Mask" (False Positives) and 6 instances where it incorrectly predicted "No Mask" when the actual label was "Mask" (False Negatives). The high number of correct predictions and the low number of errors indicate that the model has achieved a strong level of accuracy and reliability in distinguishing between the two classes for this particular experiment. This performance suggests that the model can effectively classify "Mask" and "No Mask" labels with minimal misclassification.

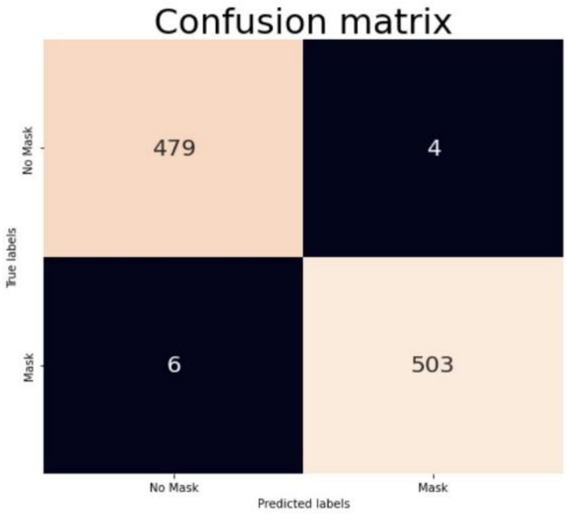

Figure 3. Confusion Matrix Experiment with 10 Epochs

Another method to assess the learning process is by examining the training graph. The validation accuracy surpasses the training accuracy, indicating a significant divergence between the two lines. This divergence is not ideal and suggests that further fine-tuning of the model is necessary. On the other hand, in the left graph, the blue lines represent the training loss, while the orange line represents the validation loss. Both losses exhibit a substantial decline during the training process. Notably, when the validation loss becomes lower than the training loss, it implies that the model can avoid overfitting, which is a positive outcome, as shown in figure 4.

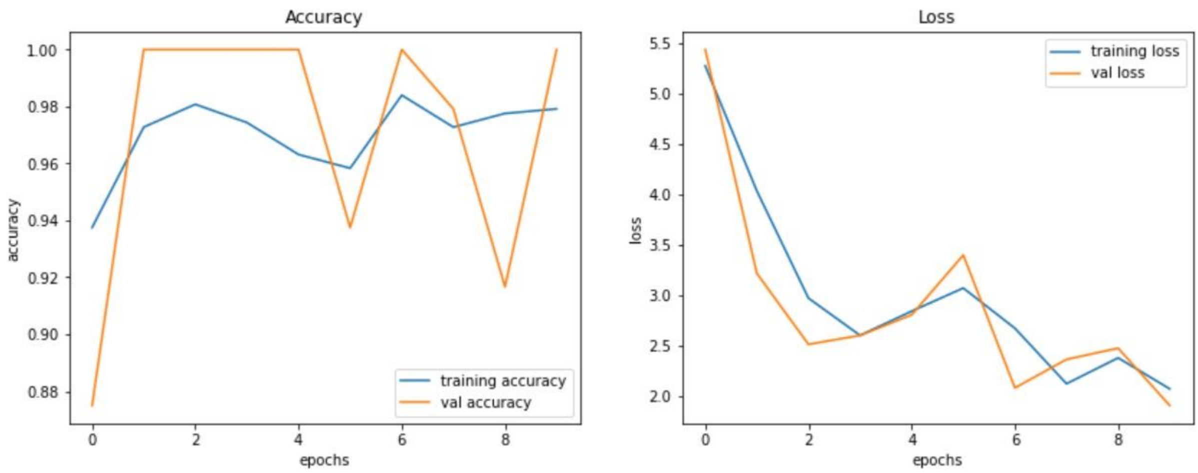

Figure 4. Accuracy and Loss Graph Experiment with 10 Epochs

The experiment used an architecture with 20 epochs, resulting in a training accuracy of 0.9744 and a validation accuracy of 0.9792 as shown ini table 2. The corresponding losses were 1.0514 for training and 1.1309 for validation. The learning rate was set to 0.001 for the first ten epochs and then reduced to 5.0000e-04 for the remaining ten (10) epochs.

Table 2. Experiment with 20 Epochs

Experiment				
Epoch	**Training Loss**	**Training Accuracy**	**Validation Loss**	**Validation Accuracy**
20	1.0514	0.9744	1.1309	0.9792

The confusion matrix shows that 482 images of people not wearing masks are correctly classified, and 502 images of people with masks are correctly classified. Eight images are wrongly classified, as shown in figure 5 and figure 6.

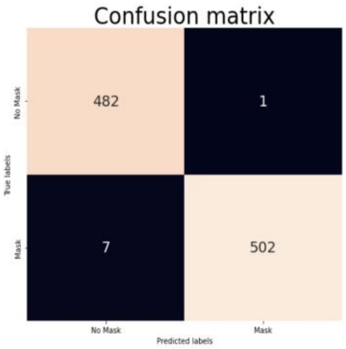

Figure 5. Confusion Matrix Experiment with 20 Epochs

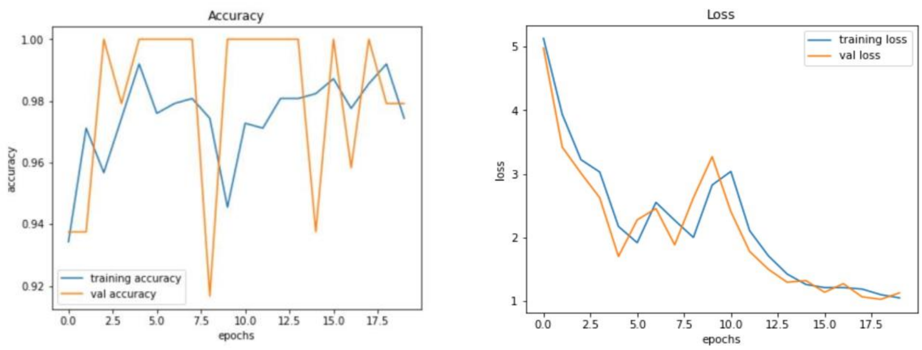

Figure 6. Accuracy and Loss Graph Experiment with 20 Epochs

The training graph displays the training loss as the blue line and the validation loss as the orange line. Both losses show a significant decline during the training process, even though in the middle, the validation loss is slightly higher than the training loss. Notably, when the validation loss becomes lower than the training loss, the model avoids overfitting. This is a positive outcome as it demonstrates the model's ability to generalize unseen data well and avoid memorizing the training data.

The experiment used an architecture with 30 epochs (see table 3), resulting in a training accuracy of 0.9856 and a validation accuracy of 0.9792. The corresponding losses were 1.0262 for training and 0.9231 for validation. The learning rate was set to 0.001 until 20 epochs and then reduced to 5.0000e-04 for the remaining ten (10) epochs.

Table 3. Experiment with 30 Epochs

Experiment				
Epoch	**Training Loss**	**Training Accuracy**	**Validation Loss**	**Validation Accuracy**
30	1.0262	0.9856	0.9231	0.9792

The confusion matrix shows that 482 images of people not wearing masks are correctly classified, 497 images of people with masks are correctly classified, And 13 images are wrongly classified (see figure 7).

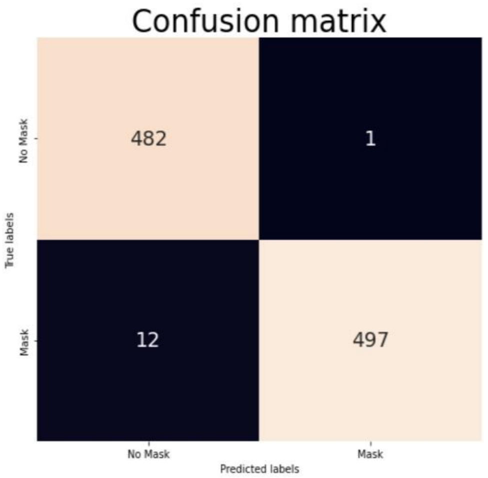

Figure 7. Confusion Matrix Experiment with 30 Epochs

In figure 8 the blue line represents the training accuracy, while the orange line represents the validation accuracy. The validation accuracy is mostly higher throughout the epochs than the training accuracy. There is a slight divergence between the two, but it is smaller than the model with 10 and 20 epochs.

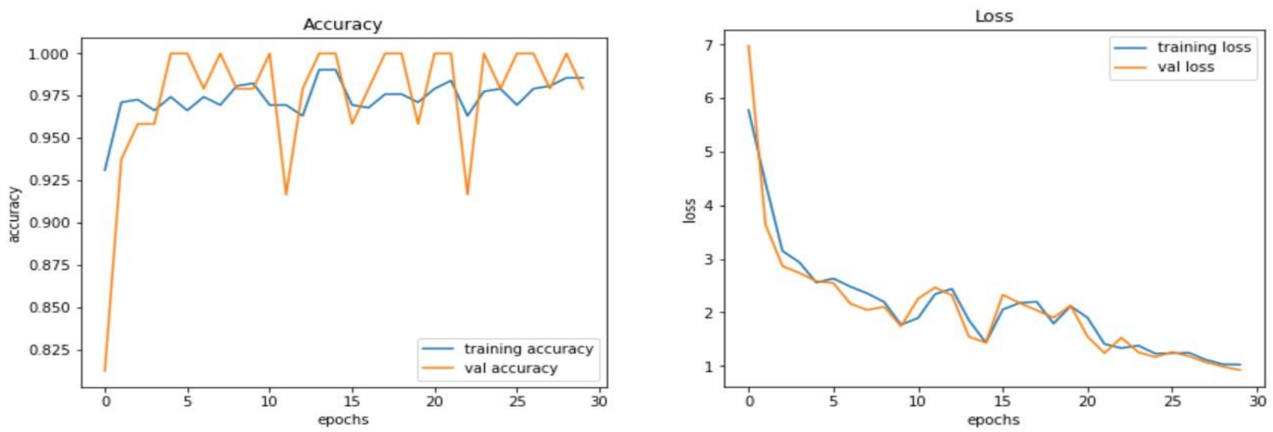

Figure 8. Accuracy and Loss Graph Experiment with 30 Epochs

4.2. Model Training Result

The MobileNet-V2 experiments based on different epochs, as shown in Table 4, reveal several key insights into the model's performance.

Table 4. Model Training Results

Result Training Model					
Experiments	**Epoch**	**Training Loss**	**Training Accuracy**	**Validation Loss**	**Validation Accuracy**
Experiment MobileNet-V2	10	2.0697	0.9792	1.9047	1.0000
	20	1.0514	0.9744	1.1309	0.9792
	30	1.0262	0.9856	0.9231	0.9792

Table 4 shows the model's performance based on different number of epochs. Initially, the training loss shows a significant decrease from 2.0697 at epoch 10 to 1.0514 at epoch 20, indicating that the model is effectively learning and improving. However, the reduction in training loss from epoch 20 to epoch 30 is minimal, suggesting that the model is nearing its optimal performance. The training accuracy remains consistently high, with a slight dip at epoch 20, but overall, it indicates that the model fits well with the training data.

The validation loss decreases steadily across the epochs, a positive sign that the model is generalizing well to unseen data. The most significant drop in validation loss occurs between epoch ten (10) and epoch 20, with a further decrease by epoch 30. However, the accuracy of the validation presents an unusual pattern. At epoch 10, the validation accuracy is perfect, which is highly suspicious and might indicate overfitting or an anomaly in the validation process. This perfect score drops slightly at epoch 20 and remains stable at epoch 30, suggesting that the model is starting to generalize better, but the initial perfect score needs further investigation.

Comparing the training and validation performance, it is unusual to see the validation loss consistently lower than the training loss. This might suggest that the validation set is easier than the training set or that there is some data leakage. The perfect validation accuracy at epoch 10 is a red flag, indicating potential overfitting, where the model performs well on the training data but fails to generalize to new, unseen data. The slight decrease in validation accuracy from epoch 10 to epoch 20 and its stability might indicate that the model is starting to generalize better. However, the initial perfect score needs further investigation.

To address these concerns, it is recommended that the validation data be investigated to ensure it is representative of real-world data and that there is no data leakage. Using cross-validation could provide a more robust estimate of the model's performance. Regularization techniques such as dropout or weight decay could also help prevent overfitting. Experimenting with different learning rates might also yield further improvements in training and validation performance.

Overall, the results at epoch 30 indicate a good balance between training and validation performance, suggesting that the model is well-trained and generalizes effectively, which obtained a validation accuracy of 97.92%. The slight decrease in validation accuracy from epoch 10 to epoch 30 is not concerning, as the perfect score at epoch ten might have been an anomaly or a sign of overfitting. As a result, this model has been selected for deployment in the real-time face mask detection prototype.

4.3. Prototype Testing Results

The selected model, MobileNet-V2 with 30 epochs, was identified as the best model for face mask detection. To validate its effectiveness, the model is integrated into a prototype developed using the 'Tkinter,' which is the standard GUI library for Python. The prototype serves as the project's graphical user interface (GUI), allowing users to test the model's capability to identify the appearance of face masks on individuals. The interface provides a user-friendly real-time face mask detection platform using the chosen model, as shown in figure 9.

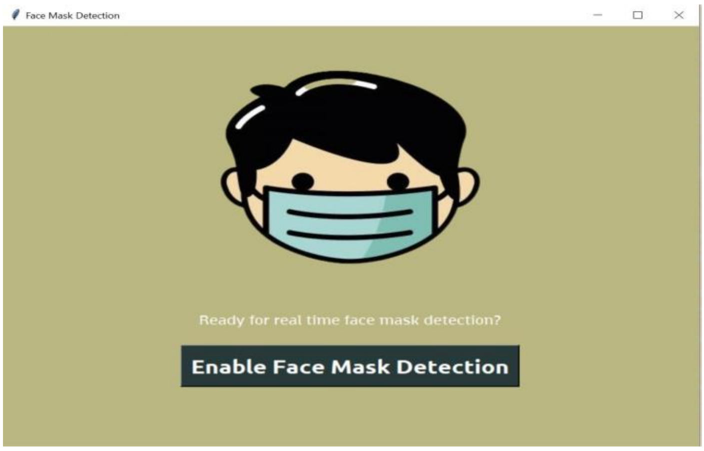

Figure 9. Prototype Interface

This page displays the prototype interface created using the Tkinter package, which provides a Python-based graphical user interface. The interface features a button labeled "Enable Face Mask Detection," which users can click to initiate real-time face mask detection. Clicking the button will activate the system to analyze live video streams for face mask presence, providing instant feedback on whether individuals are wearing masks, as shown in figure 10.

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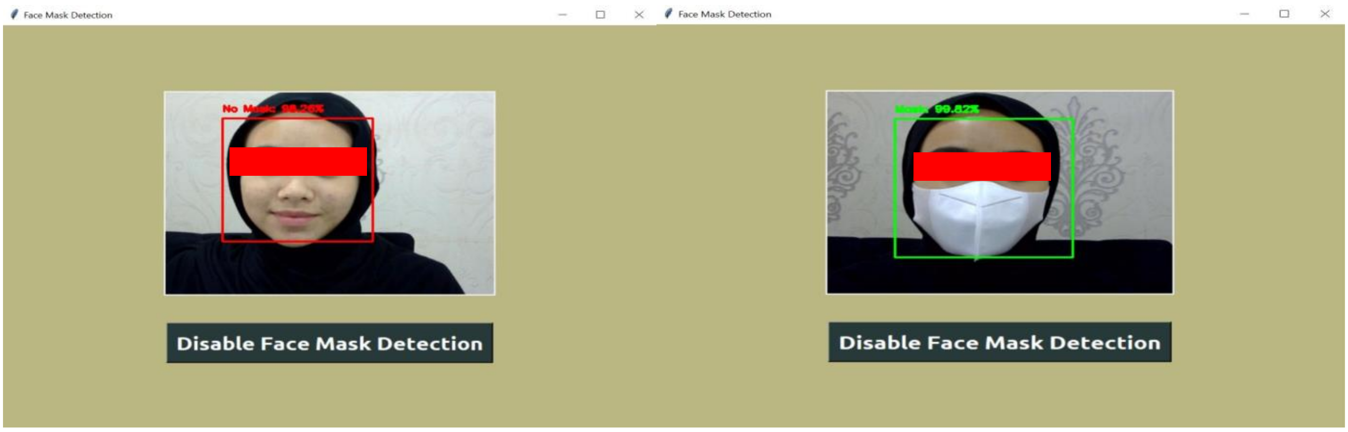

Figure 10. Example output of people with and no mask

The size of the webcam frame is kept small to ensure smooth performance during real-time face mask detection. Larger frames can cause lagging and hanging, impacting the overall detection speed. By using a smaller frame, the detection process can run more efficiently, providing a better user experience. If the user wishes to stop the face mask detection, they can click the "Disable Face Mask Detection" button. This will return them to the front page, where they can enable the face mask detection again or perform other actions as required. The "Disable Face Mask Detection" button provides a convenient way for the user to control the face mask detection process as needed. The data preparation results indicate the success of the data pre-processing and augmentation steps, ensuring the data is well-prepared for better model training. Subsequently, we conducted experiments comparing results based on the model MobileNet-V2.

5. Conclusion

The first objective is to identify the features and differentiate people with and without masks, which has been accomplished. In face and mask detection, the focus is on crucial facial features like the mouth, nose, eyes, and ears. When individuals are not wearing masks, the features focused on are the ears, mouth, eyes, and nose.

The second objective is to train the CNN algorithm to detect face masks, which has been achieved. The proposed model is used. The results at epoch 30 indicate a good balance between training and validation performance, suggesting that the model is well-trained and generalizes effectively, which obtained a validation accuracy of 97.92%. The slight decrease in validation accuracy from epoch 10 to epoch 30 is not concerning, as the perfect score at epoch ten might have been an anomaly or a sign of overfitting. This selected model is considered the most optimal choice for deployment in real-time face mask detection applications, offering superior performance and accuracy compared to the other models.

The third objective is to develop a face mask detection prototype using a CNN. The prototype's main objective is to determine whether an individual is currently wearing a face mask. The prototype is developed using Tkinter, the standard GUI library for Python. The platform chosen for this prototype is a laptop, and real-time input images are received from the laptop's external webcam for the face mask detection process. The prototype classifies the appearances of face masks into two categories: "mask," which indicates an individual with a mask, and "no mask," which indicates an individual without a mask.

It is crucial to collect additional data in the future to enhance the model's capability of detecting individuals who improperly wear face masks. By incorporating this new data into the training process, the model can be improved and better equipped to identify instances where individuals are not wearing masks properly. The increased dataset will enable the model to learn from diverse examples, leading to more accurate and reliable detections in real-world scenarios.

Due to hardware limitations and time constraints, exploring and evaluating other CNN models for face mask detection was not feasible. However, with access to better GPU resources, conducting more comprehensive experiments by training models with larger datasets and exploring a wider range of CNN architectures is possible. These efforts could further advancements in face mask detection and uncover even more effective models.

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The project has successfully achieved its first, second, and third objectives. The desired techniques have been implemented, and a prototype desktop version of the product has been developed. However, various aspects of the project still need to be enhanced. One notable improvement is developing a web-based application, offering users greater convenience and accessibility. By transitioning to a web-based platform, the product can reach a wider audience and provide a seamless user experience.

6. Declarations

6.1. Author Contributions

Conceptualization: F., T.B.K., D.A.D., M.Z.Z., P.A.A.; Methodology: D.A.D.; Software: F.; Validation: F., D.A.D., dan P.A.A.; Formal Analysis: F., D.A.D., dan P.A.A.; Investigation: F.; Resources: D.A.D.; Data Curation: D.A.D.; Writing Original Draft Preparation: F., D.A.D., dan P.A.A.; Writing Review and Editing: D.A.D., F., dan P.A.A.; Visualization: F.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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