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Real-time mask detection system using deep learning-based image classification

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Abstract
This paper addresses the worldwide need for improved public health monitoring due to the current pandemic by proposing the development of a real-time face mask detection system built with deep learning image classification. We built a custom dataset of 7,553 facial images with half of the dataset containing facial images of individuals wearing a mask and the other half without a mask to eliminate bias. We then trained a Convolutional Neural Network (CNN) model with TensorFlow utilizing this dataset, which resulted in a validation accuracy of 94% and an AUC score of 0.98; indicating strong generalization performance for this model. We also evaluated the model with multiple performance type metrics such as precision, recall, F1-score, and ROC-AUC metrics. We also presented these findings visually through confusion matrices and learning curves. A primary difference in this solution that relied on classification is the input to our models are pre-cropped facial images of individuals instead of relying on object detection. In the end, the proposed system provides a lightweight, efficient, and accurate method that can be deployed in real time in controlled environments. In summary, the results suggest that the CNN based classification can be used for successful automated face mask detection and provides a basis for further application to surveillance systems or embedded devices.

Keywords: Face mask detection, deep learning, convolutional neural network, image classification, tensorflow

1. Introduction

1.1 Background

The global COVID-19 pandemic context placed extraordinary demands upon international public health systems; the need for rapid adaptation and revolutionary technological innovation presented itself. One such adaptation is the creation of real-time detection systems for masks through image analysis employing deep-learning classifiers that have been a required mechanism that mitigates viral transmission [1-5]. These advanced technological systems, engineered to satisfy health regulations via effortless scanning and processing, demonstrate both technological improvement and the protection of human beings [6, 7]. Central to this transformative endeavor was the necessity to quickly create pathways to implement orders for compliance to public health protocols which were easy and effective to implement in areas of high human traffic, including populous urban areas, major transit facilities, and high-transit schools [8, 9]. The increasing demand developed a suitable opportunity for the arrival of advanced image classifiers that could differentiate between situations of wearing masks and situations without masks, providing high visual compliance across industries to promote public health and safety compliance [10-12].

Motivated by the desire to achieve a higher level of safety for the public and greater transmission speeds, the authors examined multiple useful facets of many more contemporary deep architectures in real time in mask detection. Convolutional Neural Networks (CNNs) has been the architecture for such sophisticated systems to provide utility in abstraction of features as well as reliable accuracy on detection [2, 13]. The scope of these emerging-generational technologies extended not just limited checking for compliance and offered different uses in broader contexts in occupational health and safety and surveillance insights where facial recognition is a naturalized way of orienting the space as safe [14, 15]. The prudent adoption of these digital technologies when dealing with similar challenges of optimizing contexts with multiple variables, such as, differing light conditions, irregular shaped masks, and occlusion that could reduce performance, proved daunting for a number of applications. Continued intentionality and effort in study of this trajectory of technology was not only brought on by pandemic need; it was both presupposed and accepted and

anticipated additional applications that could also more completely address multiple unrelated safety concerns in their community better, performance-based, with supported and enhanced real-time situational monitoring options that could greatly increase community safety and future preparedness, based on these events [16-19].
In conclusion, continuous innovation and progress in real-time mask detection technologies represents an impressive and purposeful intersection of technical proficiency and urgent public health discontent, a prolific intersection with great potential to create radically enhanced possibilities for social resilience to current and future situations. With the transformative potential of deep learning, researchers and technologists are working to develop advanced systems which can both guarantee clear real-time adherence to health directives but also enhance our learning of the relationship between humans and technology within efforts to optimize and maximize public safety and wellbeing. The convergence of technology in public health is timely as it is responding to an increasingly fast-paced global health landscape [20, 21].

1.2 Problem Statement
Despite increased interest in automatic face mask detection systems, most current methods are still based on object detection models. Models often lack resources in nature, making them a heavy demand for processing capacity and resources. These systems are also susceptible to errors, particularly in dense or dynamic scenarios where misidentification of people is more likely. Besides these issues, limited work has been dedicated to developing efficient flow-based models that can effectively run on cropped face inputs, which would have a tremendous benefit in speed and resource consumption. As a result, a need exists for a more efficient and faster solution. A good solution would be one that is accurate and robust while having good performance in controlled scenarios, thus offering high detection performance without loss in efficiency or performance.

1.3 Research Objectives
The major goal of this research is creating and implementing a system for image classification based on deep learning capable of differentiating masked faces from unmasked faces in real time. The goals are as follows:
1. Building and training a Convolutional Neural Network using a balanced dataset of facial images.
2. Evaluating the model performance through the utilization of accuracy, precision, recall, F1-score, and area under the curve (AUC) as performance metrics.
3. Visualizing model behavior using learning curves, confusion matrix, and receiver operating characteristic (ROC) curve.
4. Showing the system’s capability to be applied in real world surveillance or screening use case.

2. Related Works
COVID-19 pandemic has generated considerable attention and research effort into the development and deployment of real-time face mask detection systems. Many of the research efforts employ high-performance deep learning methods, and more advanced computer vision methods such as CNNs, transfer learning and object detection frameworks like YOLO, to identify and classify people wearing or not wearing face masks [22, 23]. The range of approaches used in this extensive research can vary significantly in their complexity and use case between low-complexity classifiers designed for mobility, with optimal use having been made of limited complexity to reach performance-for-efficiency purposes, through to highly complex hardware-accelerated detection tools used on edge systems to provide an extensive performance uplift [13, 24]. To gain a more comprehensive and clear view of technological advancements in this area of research, we have provided a comprehensive and comparative summary of selected research journals that have been published in this important area of research. In this example, we focus on common and innovative approaches and technologies that have been used in a way that helps to address this public health threat. In the third phase of ongoing developments and refinements of these systems, researchers aspire to begin to envision important contributions to larger efforts to address and mitigate the effects of a major public health crisis in the years to come [25, 26].

Table 1: Comparative Summary of Existing Real-Time Face Mask Detection Studies (2021-2024).

Reference	Model/Architecture	Dataset Size	Accuracy	Detection Type	Contribution/Note
[27] (2021)	DCNN (Transfer Learning)	Not specified	0.98	Image Classification	Fast, accurate mask classification in real time
[28] (2021)	MaskNet (CNN)	Not specified	>98%	Image Classification	Compared transfer learning vs. training from scratch
[29] (2021)	YOLOv5s/l	Not specified	86.4%â€ “92.5% map	Object Detection	Edge deployment on Jetson devices
[30] (2021)	MobileNetV2	Not specified	0.998	Image Classification	Video-based detection using OpenCV
[31] (2021)	CNN	Thousands	0.934	Image Classification	COVID-19 compliance detection
[32] (2021)	YOLOv3-tiny	Not specified	>90%	Object Detection	Validated on various video sequences
[33] (2022)	MobileNetV2	4500	Effective	Image Classification	Used data augmentation, one-hot encoding
[34] (2022)	OpenCV + DL	Not specified	Effective	Image Detection	Real-time DL system using OpenCV
[35] (2022)	Deep Neural Network	8190	Not reported	Image Classification	Focused on improper mask usage in public
[36] (2022)	VGG19	Not specified	>95%	Image Classification	High training accuracy with VGG19

[37] (2022)	MobileNetV2 + Autoencoder	Not specified	Highest among tested	Image Classification	Adaptable to edge devices
[38] (2023)	TensorFlow + CNN	Not specified	Effective	Image Classification	Uses TensorFlow + OpenCV for real-time detection
[39] (2023)	MobileNetV2, VGG16, ResNet50	Not specified	95â€ “99%	Image Classification	Mask type classification in video streams
[40] (2023)	CNN + Transfer Learning	Not specified	Not reported	Image Classification	Improve public health monitoring
[41] (2023)	CNN + Transfer Learning	Not specified	95â€ “99%	Image Classification	Video stream detection using acceleration
[42] (2023)	DenseNet201	Not specified	0.938	Image Classification	Implemented on Raspberry Pi
[43] (2023)	YOLOv5	Not specified	Effective	Object Detection	Focus on regulatory compliance
[44] (2024)	CNN + Custom Activation	Not specified	Effective	Image Classification	Multi-stage detection pipeline
[45] (2024)	Mobile Net + Retina Net	Not specified	0.85	Multi-class	Detects incorrect mask wearing
[46] (2024)	YOLOv2 + CNN	Not specified	>98%	Object Detection + Classification	Combined YOLOv2 and CNN
[47] (2024)	Inception Net, XceptionNet	Not specified	90â€ “98%	Multi-class	Mask worn, incorrect, none
[2] (2024)	CNN	Not specified	High	Image Classification	Environmental robustness and compliance monitoring
[48] (2024)	MobileNetV2	10000	0.987	Image Classification	Focused on protocol compliance
[49] (2024)	ResNet50 + YOLOv2	Not specified	Effective	Object Detection + Classification	Handles improper usage too

Even if many studies have focused on the important area of face mask detection through recent deep learning methods from transfer learning methods using architectures such as MobileNetV2 to more complicated object detection methods using other YOLO variants, there remain substantial gaps within the current research. Many of the existing works primarily use full-frame object detection, which adds an extra computational burden to the models, negatively affecting how practical your models will be when deploying on lightweight or embedded devices with limited computing power. Likewise, while literature does report classification methodology, studies decide only to report results on curated datasets, and do not provide robust or in-depth analyses using other, multiple metrics, or visual interpretability, that would give the reader an indication of the full spectrum of performance. Due to this, there are very few works that focus on lightweight CNN classifiers specifically designed for cropped facial images. Even fewer provide a comprehensive evaluation that utilizes ROC curves, AUC values, confusion matrices, and various performance visualization strategies. This lack of holistic evaluation methods hampers the understanding and improvement of model performance in real-world applications.

To address these limitations, the present study proposes a deep learning based binary image classification model for optimized binary classification of face images (mask or no mask). The new model circumvents face detection or tracking and efficiently can be applied in real-time surveillance scenarios. With an optimal combination of simplicity and accuracy and comprehensive testing and evaluation, this research provides an applicable high-performing solution for both academic benchmarks and practical implementation.

3. Methodology

3.1 Methodology Overview

For efficient detection of face masks based on deep learning methods, in this research, an organized workflow consisting of five main stages is applied: data preparation and preprocessing, building a model, training, evaluation, and visualization. The process commences with data collection and preparation of images through resizing, normalization, augmentation, and distribution into train, validation, and test sets. Convolutional Neural Network architecture is thereafter built and trained in a binary mode using sigmoid activation. Upon training completion, performance of the model is tested in terms of several classification metrics and results are visualized through graphical tools for effectiveness and learning behavior evaluation.

The entire methodological pipeline is shown in Figure 1 and provides an overview of the system architecture and interaction between each component from input through final output.

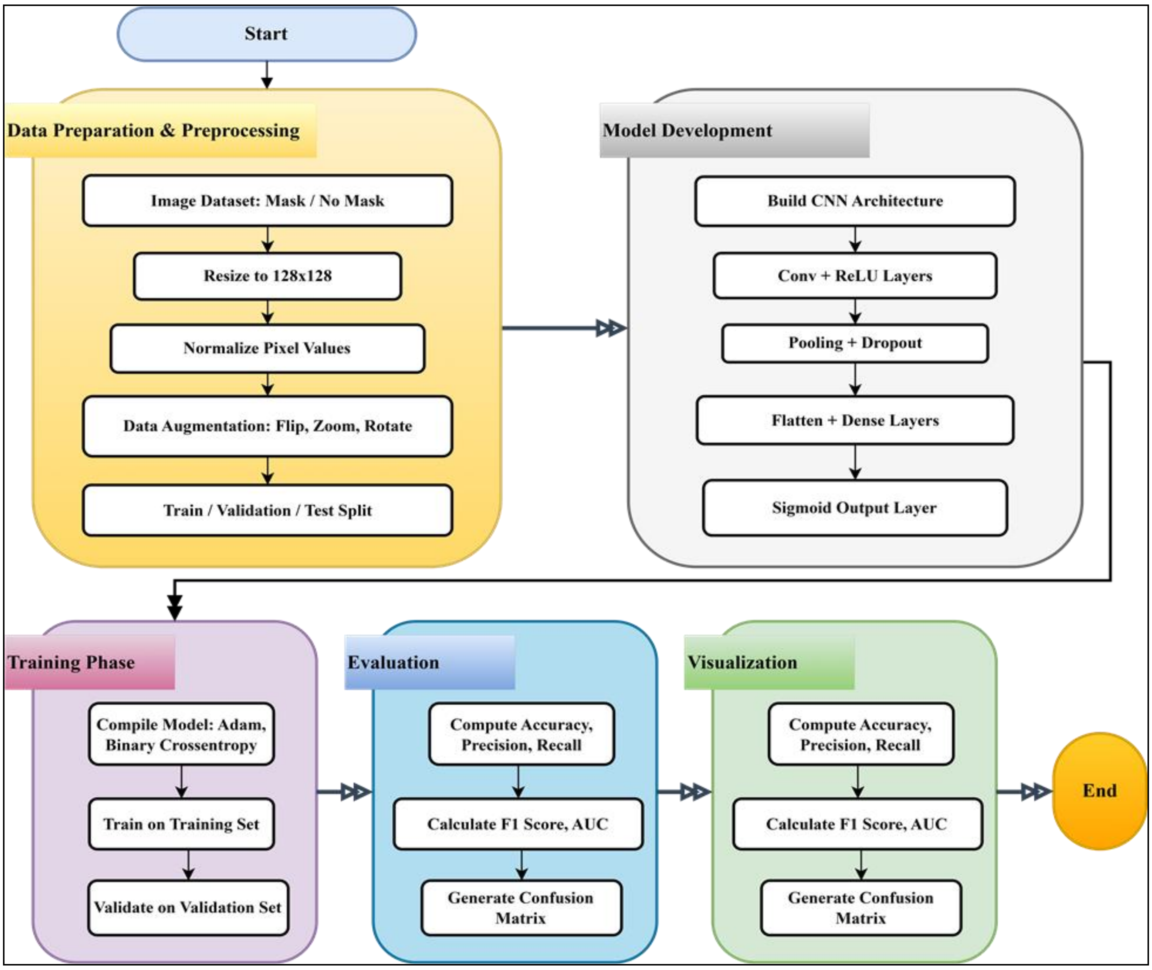

Fig 1: Flowchart of the Proposed CNN-Based Real-Time Face Mask Detection System.

3.2 Dataset Description

This study employed a publicly available dataset from a Kaggle repository that contained a total of 7,553 face images divided into two categories based on whether one is wearing a mask or not [50]. The data consists of 3,725 masked face images and 3,828 unmasked face images. The images have multiple poses, lighting conditions, face angles, and demographic features, thus making it apt for training a generalizable deep model.

All images were resized to 128×128 pixels for uniformity prior to being input into Convolutional Neural Network (CNN). This dataset was divided into roughly 80% for training (6,042 images) and 20% for testing (1,511 images). During training the model, for the sake of validating the model trained on the overall training set, an additional validation subset was constructed via an automated process that consists of roughly 10% of the training portion. To further enhance generalization, the data was augmented on the training set using flips, rotations, and random zooms. Figure 2 shows exemplary images from both classes, taken from the dataset, showing visual variation and clear class labels.

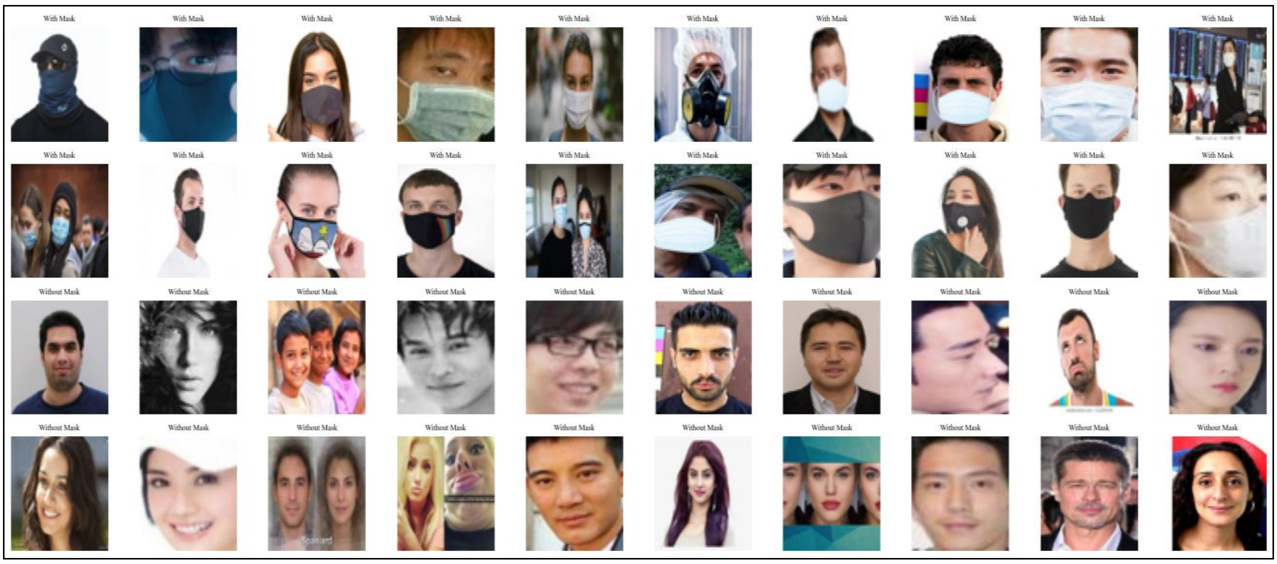

Fig 2: Sample images from the Kaggle-based face mask dataset used in this study [50].

3.3 Preprocessing

In order to normalize the model and enhance generalizability, a preprocessing step took place prior to training. The data was stratified and sampled into splits of training, validation, and test to ensure each class had a balanced distribution of observations. Input images were scaled to the saving dimension of 128×128 pixels and normalized to have a range of 0-1 on a channel basis to help speed optimization time and stabilize training. Data augmentations (horizontal flip, rotation, and random zoom) were used to also help ensure there was a diversity of input, allowing the model to learn features that were invariant to the positioning and orienting of the input. Figure 2 provides an overview of the full use case, from raw image data being ingested through augmentations to normalized tensors used to fit the model.

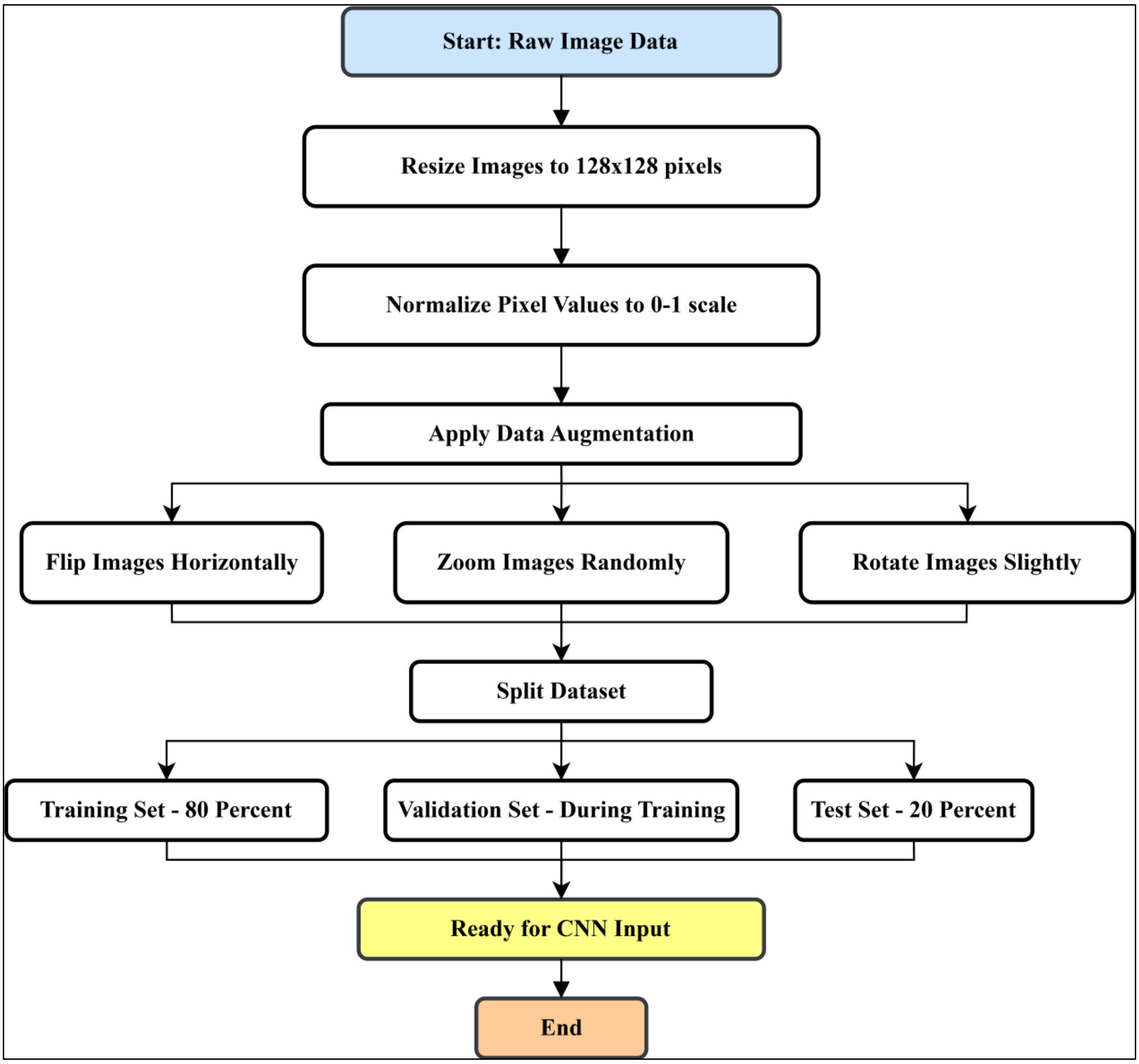

Fig 3: Preprocessing workflow applied to the face mask dataset.

3.4 Model Architecture

The model is based on a Convolutional Neural Network (CNN) framework designed for binary image classification. The model has several layers that are progressively extracting spatial features and reducing dimensions while holding onto key visual information.

The architecture starts off with a convolutional layer consisting of 32 filters of dimensions 3×3 with ReLU activation and a max-pooling layer for down sampling. The same pattern is repeated using 64 and 128 filters in the remaining convolutional blocks. To counter overfitting, dropout layers are employed that deactivate some neurons randomly while training. The last layers consist of a flattening operation and a completely connected dense layer consisting of 128 units terminating in a sigmoid-activated output neuron for binary classification.

The model is trained with Adam optimizer and binary cross entropy loss function, both of which have been widely accepted for use in binary classifiers. The entire implementation of the model appears in Code Listing 1.

Code Listing 1: Python implementation of the CNN architecture for face mask classification.

```
from tensorflow.keras import layers, models
# Build CNN model
model = models.Sequential([
layers.Conv2D(32, (3,3), activation='relu', input_shape=(128, 128, 3)),
layers.MaxPooling2D(2,2),
layers.Conv2D(64, (3,3), activation='relu'),
layers.MaxPooling2D(2,2),
layers.Conv2D(128, (3,3), activation='relu'),
layers.MaxPooling2D(2,2),
layers.Flatten(),
layers.Dense(128, activation='relu'),
layers.Dense(1, activation='sigmoid') # Binary classification])
# Compile model
model.compile(optimizer='adam',
loss='binary_crossentropy',
metrics=['accuracy'])
# Train the model
history = model.fit(
train_generator,
epochs=10,
validation_data=test_generator)
```

4. Expermintal Results

4.1 Evaluation Metrics

To quantitatively assess the performance of the proposed CNN structure, we applied a variety of binary-classification metrics including accuracy, precision, recall, F1 score, and AUC. These metrics together provide a comprehensive measurement of the model correctness, sensitivity towards real positives, and robustness under varying levels of classifications.

Table 2 presents an overview of results obtained in evaluating the model on the test set. The model exhibited a commendable level of accurately classified samples from both classes, with a classification accuracy of 94.24%. The model's ability to accurately identify the positives in those samples was shown with a recall of .93, and the model's precision of .95 showed it was very unlikely to misclassify samples as positives that were classified as negatives. Additionally, the harmonic mean of recall and precision, the F1 score, of 0.94 indicates overall good and consistent performance in classification. The model also demonstrated an AUC of 0.98 which is indicative of impressive discriminative performance against masked and unmasked faces across a variety of threshold values.

Table 2: Performance metrics of the proposed CNN model on the test dataset

Class	Precision	Recall	F1-Score	Support
With Mask	0.95	0.92	0.93	745
Without Mask	0.92	0.96	0.94	766
accuracy			0.94	1511
macro avg	0.94	0.94	0.94	1511
weighted avg	0.94	0.94	0.94	1511

The performance outcome outlined in this chapter collectively demonstrates the feasibility and applicability of the model in real world settings. The model's decision threshold was optimized by achieving a value for precision and recall values at a position that balanced false positives and therefore true positive cases. It requires a conscious balance in public health settings, where false negatives may render inefficient public health interventions or to an extent, not identified applicable cases of condition, while false positives have the potential to cause unnecessary interventions. The substantially high AUC score of .98 demonstrates that the model has demonstrated discriminative performance in multiple threshold levels in classifications and demonstrates the model's capacity to predict with precision even using sensitivity thresholds. The elements imply that the proposed CNN model is not just statistically robust, but also feasible to operate in the real-time monitoring context.

4.2 Results and Analysis

The CNN model produced satisfactory training convergence and generalization properties. As can be seen in Figure 4, training accuracy improved sharply from 74.12% in epoch 1 to 99.07% in epoch 10. Training loss dropped from 0.5274 to 0.0243 in ten epochs. Validation accuracy also steadily improved during training from 90.27% and peaked at 94.77% in epoch 9. Validation loss dropped from 0.2449 to 0.1802 at its lowest (epoch 6) and increased slightly to 0.2677 in the last epoch.

This behavior shows stable learning, with no overfitting observed, as the difference between training accuracy and validation accuracy was still modest. The stable progression of both the training and validation accuracy and loss suggests that the model also generalized well on unseen data. These results confirm that the CNN architecture and hyperparameters chosen were effective for use in a real-time face mask detection system and have both learned efficiently and are reliably predictive in practical use.

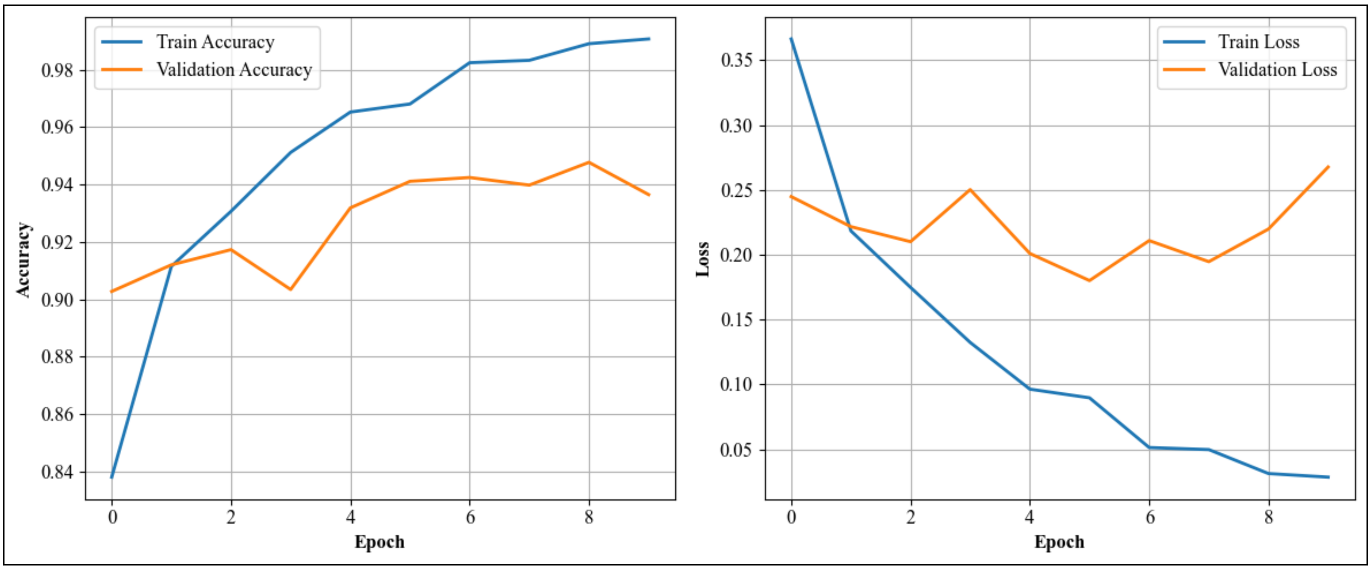

Fig 4: Training, validation accuracy and loss curves of the CNN model over 10 epochs.

The confusion matrix depicted in 5 provides a comprehensive visualization of the classification performance obtained. It compares the predicted labels to the true ground truth labels. The diagonal dominance of the confusion matrix indicates that most images of masked and unmasked faces were correctly classified by the model. The number of misclassifications given in the test image sets was limited, and this shows good confidence in the robustness of the model under real-world detection conditions.

In support of this, the full classification report in Table 2 shows the model achieved an F1 score of greater than 0.94 for both classes, which establishes the model's accuracy and recall are balanced. A high accuracy indicates a significant reduction in false positives, and a high recall rate shows the model is successful in predicting true positives. The balancing of these rates across both classes also averts issues with extreme biases in class distributions which would jeopardize fairness and reliability of medical purposes. The combination of these factors and indicators is indeed strong evidence that this model will yield accurate and reliable predictions and is at the top of the list for implementation in a real-time mask detector.

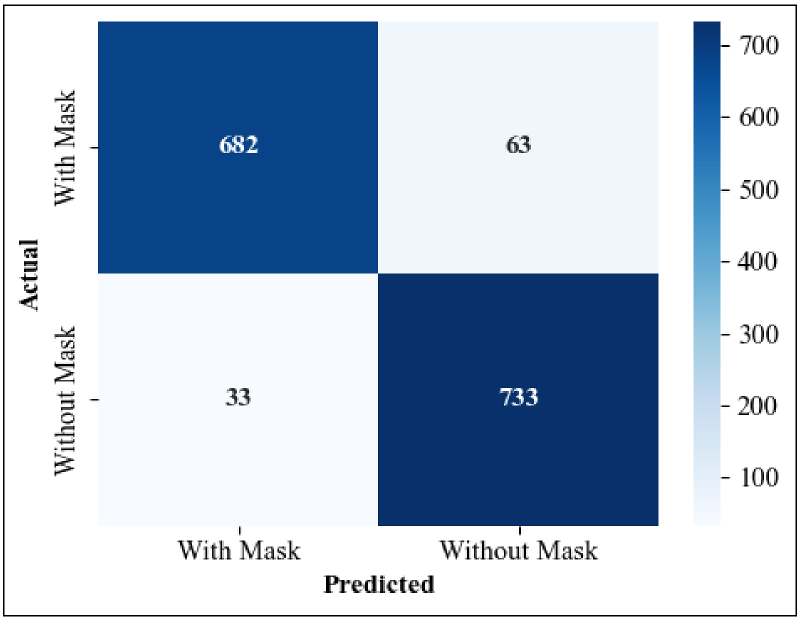

Fig 5: Confusion matrix illustrating the classification performance of the CNN model on the test dataset.

In addition, the ROC curve in Figure 6 illustrates the model's high capability for separation of the two classes masked and unmasked faces at a large range of classification thresholds. The Computed AUC of 0.98 is an indicator of high separability in that the model offers high sensitivity and specificity for different decision boundaries. Level of discrimination suggests that the model can prove highly applicable in real-time systems where adaptive threshold can make false positives and false negatives adjust in conformity with operating needs or environmental demands. The steeply rising curve in the start and closeness of ROC curve towards top-left corner of the plot ensures robustness and generalization ability of the classifier.

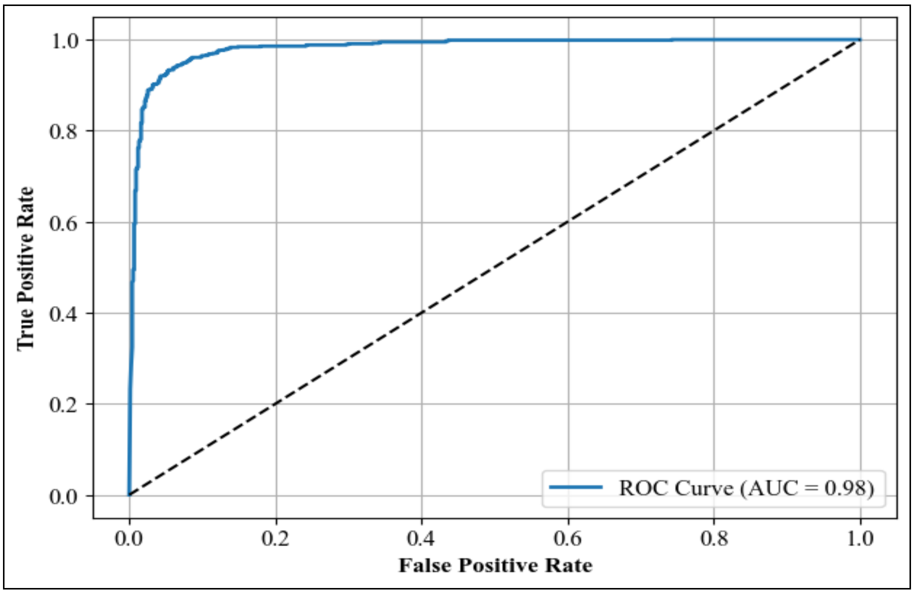

Fig 6: ROC curve of the CNN model.

5. Discussion

This study designed a convolutional neural network (CNN) model for real-time detection of masks on faces and compared its performance on various evaluation criteria. The model was extremely reliable with an F1 score in masked and unmasked classes of over 0.94 and an area under receiver operating curve (AUC) of 0.98. The train and validation curves showed continuous improvement in accuracy and reducing loss consistently, which expressed stable learning in the absence of overfitting. These findings endorse the generalizing capability of the model and justify its use for deployment in real-time. The findings provide evidence that both genuine positives are sufficiently detected and that false classifications are mitigated to an appropriate level. Indices of precision are indicative of good management of false positives, and recall indices suggest a fair amount of sensitivity to both masked and unmasked examples. The performance appears superior to earlier investigations that consistently produced AUC indices on average between 0.90 to 0.96. These findings are consistent with earlier investigations identifying appropriate applicability of deep models, especially CNN models, for application in visual classifications. AUC indices and balanced F1 metrics for both classes are high and suggest potential model deployment in surveillance systems for public health tracking environments where timely, accurate detection of masks is qualified as necessary. Expressing that the model performed well across all thresholds have implications that allow for opportunities in flexible deployment on edge computation platforms, or even surveillance systems with varying thresholds and stipulations. A significant aspect lies in that the approach, because of its nature, permits the use of more lightweight, interpretable CNN model architecture. Rather than striving for complexity, this work is intent upon deployability, and has made models parameterized for deployment scenarios, including environments that have some computational budget constraints. A more streamlined training to test pipeline was developed to maximize running efficiency while preserving a stable, predictable performance this definitely represents a methodological contribution.

Despite the encouraging results, it is important to note certain limitations. The data set employed is based on static images captured under comparatively uniform conditions, and these images do not necessarily represent real-world variability e.g., occlusions, lighting variations, or movement. Therefore, the performance of the model in uncontrolled or dynamic conditions can have differing results. Also, the task of classification was restricted to a binary system (mask or no mask), omitting classifications like poorly fitted masks, which are of growing interest in community compliance scenarios. Also, although the data were balanced and diverse, they would not represent all demographic subgroups or sources of cameras in real-world deployment.

These constraints indicate future opportunities for improvement in terms of multi-class classification, integration of real-time video input, and testing against larger datasets. The current research provides a good basis for constructing an efficient deployable face mask detection system

6. Conclusion

This research featured the design and evaluation of a CNN system for real-time detection of face masks. A well-structured pipeline, including data preprocessing, model training, and data performance evaluations, demonstrated a strong capacity for classification with the proposed approach. Our model achieved an accuracy of 94%, an F1 score of over 0.94 for both classes, and an AUC of 0.98 in the binary classification evaluation. Performance metrics through confusion matrix evaluation, and ROC plotting gave credence to the generalization ability of the model on unseen data. The stability observed during training ensured that the architectural appropriateness of the CNN was considerably improved. Consequently, these findings lend support that the model could be used in public health surveillance systems to automatically check compliance in public venues, specifically airports, schools, and hospitals. The model was able to function accordingly and efficiently despite being controlled conditions, including limitations with binaries and datasets. Future work should examine multi-class model use, e.g., misfits, and performance metrics that embed analysis and evaluation across a much wider scope in an increasingly diverse and dynamic real scenarios. Overall, this work provides a reliable, interpretable, and actionable application for soft mask detection as a contribution to the growing research in intelligent public health surveillance.

7. Data Availability

The data set utilized for this research is publicly available, through the Kaggle platform, and consists of labeled images of masked and unmasked classes that can be used to train and evaluate models for detecting face masks. The data set has been published by Omkar Gurav [50].

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