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RESEARCH ARTICLE

Face Mask Detection and Alerting System Using Transfer Learning

Kamala Challa[1]*, B Srivani[1], S Renudeepti[1], G Aakash[1]

1 Department of Information Technology, VNR VJIET, Hyderabad, Telangana, India

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* **Corresponding author**.

kamala_ch@vnrvjiet.in

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Abstract

Objectives: The aim of the proposed method is to establish an advanced transfer learning-integrated face mask identification system with improved real-time accuracy and alerting capabilities. Enhancing face mask detection reliability and ensuring timely notifications are the main goals in order to encourage adherence to health guidelines. **Methods:** By modifying pre-trained convolutional neural networks for face mask detection in real-time video feeds, our method makes use of transfer learning. Using a specific dataset, the pre-trained models are refined as part of the technique to maximise their mask detection ability. Comprehensive feature extraction and categorisation components are part of the system architecture, and when non-compliance is found, an alert mechanism is included to notify users or administrators. **Findings:** The designed system functions well in real time and exhibits 95% accuracy in face mask detection in a variety of contexts. The performance of the optimised CNN models outperforms that of traditional methods, enabling prompt and accurate identification of mask usage. **Novelty:** This study presents a novel approach to detect people with 'No Mask' irrespective of their type and alerting the authorities by using advanced machine learning approaches. Since transfer learning uses pre-trained weights, it has given a slight edge in getting accurate results comparatively to any other machine learning algorithms.

Keywords: COVID19; OpenCV; Face Mask; Transfer Learning; Accuracy

1 Introduction

Transfer learning, a concept derived from artificial intelligence, helps to utilise the pre-trained weights of the millions of images it has been trained, which can be used or incorporated into our work, to make the model work efficiently and provide accurate results for our data. Through the use of knowledge found in assorted but associated source domains, transfer learning aims to enhance the efficiency of target learners on target domains. As a result, the reliance on a large number of target-domain data for constructing target learners can be reduced. Transfer learning has become a prominent and promising area of machine learning due to its broad application prospects. Despite the fact that there are some precious and striking surveys on transfer learning, these surveys introduce approaches in a relatively isolated manner and lack recent advances in transfer learning.

It's important to keep in mind that any mask is better than none at all when using masking as a vital public health tool to stop the spread of COVID-19. The CDC continues to recommend that wear the most protective mask consistently that fits well for them to protect themselves and others from COVID-19. When worn consistently and correctly, masks and respirators are effective at reducing transmission of SARS-CoV-2, the virus that causes Covid-19. All masks and respirators offer some degree of protection, but properly fitted respirators offer the best level of security. Wearing a highly protective mask or respirator may be especially important in high-risk situations or for people who are predisposed to severe disease.

Amit et al.[1] foreground the problems faced by healthcare workers post-vaccination. During the first few days after immunisation, symptoms of COVID-19 can be confused with vaccine-related side effects. Clinicians should not dismiss post-vaccination symptoms as vaccine-related and should test for COVID-19 as soon as possible. Similarly, Fernandes et al.[2] identified the necessity of newer and more adaptable diagnostic techniques in order to identify SARS-CoV-2 infections due to the emergence of novel and evolving SARS-CoV-2 variants. However, developing fast and acute diagnostic technologies is becoming more difficult due to materialising variants and changing symptoms displayed by effected individuals. The authors reviewed the impact of emerging COVID-19 variants on diagnostic and therapeutic strategies, which included the necessity for effective face mask detection as part of broader public health interventions.

Efficient diagnostic tools are in high demand, as rapid and large-scale testing is critical in patient management and disease control. Details of the various methodologies and mechanisms of action, as well as their application range, known performance characteristics, and the significance of specimen collection timing and type is discussed, as well as disease chronicity, setting, and approaches, are presented in Safiabadi Tali et al.[3] It provided a comprehensive review of the tools and techniques available for SARS-CoV-2 detection, noting the growing role of advanced technologies, including deep learning methods, in enhancing detection accuracy. This review highlights interesting events that occurred during the pandemic and the lessons that were discovered, even though the SARS-CoV-2 literature is rapidly evolving. Exploring a broad arsenal of SARS-CoV-2 detection techniques will secure constant diagnostic support for clinicians to control and prevent infection for this pandemic, as well as advice for future pandemic preparedness. This aligns with the findings of Zhuang et al.[4], who conducted a detailed survey on transfer learning, emphasising its potential in improving various applications, including face mask detection systems.

Sethi et al.[5] proposed a novel approach involving an ensemble of one-stage and two-stage detectors in order to detect the person with 'No Mask'. Each stage of object detectors works similar to each other, but the accuracy and time efficiency are quite different. Whereas one-stage detectors are very fast and generate low accuracy compared to two-stage detectors, which are slow to train but give higher accuracy compared to one stage. So, the authors have used a combination of these object detectors along with the transfer learning models such as ResNet, AlexNet, and MobileNet along with a bounding box transformation, in order to improve the accuracy of the model and significantly reduce the time inference. The authors have observed remarkable results by using transfer learning along with the proposed technique, which has yielded an accuracy of 98.2% when worked with ResNet-50, with the precision and recall being 11.07% and 6.48% for detecting the persons who are not wearing masks, which is quite higher comparatively to the popular baseline model. As for the future scope, the authors have proposed a more effective model of detecting the face landmarks, which can also be used for face mask biometrics, along with integrating the model with video surveillance cameras to perform real time detection.

Mohammed Ali et al.[6] presented some techniques and methods involving detecting a person who is not wearing masks. The authors have put more emphasis on giving a review on how face masks are vital, help in saving millions of lives, and help in avoiding a 70% chance of getting infected by the virus. As face masks have become very vital in protecting ourselves, many government agencies have put mandatory precautions on this. So, the authors have made a literature survey on a reliable software monitoring system to detect the face mask on a person using artificial intelligence and image processing techniques. In this paper, the authors have given a short literature survey on different algorithms and how they perform on face mask detection. The algorithms that are reviewed by the authors are convolutional neural networks, which are a type of deep neural network, and yolo, which is a very popular object detection model that uses bounding box transformation to identify and detect the object. Region-based Convolutional Neural Network (R-CNN), Fast Region-based Convolutional Neural Network (Fast R-CNN), Faster Region-based Convolutional Neural Network (Faster R-CNN), Mask Region-based Convolutional Neural Network (Mask R-CNN). Each algorithm mentioned above has disadvantages and advantages, and they are differentiated by one-stage object detectors and two-stage object detectors.

Mohammed Nur Yasir Utomo et al.[7] used a simple machine learning algorithm, i.e., a soft margin support vector machine, in order to classify whether the person is wearing a mask or not. Support vector machines are very powerful and popular machine learning algorithms that can be used for object classification and also used for classifying data points, especially when the data points are linearly separated. The major reason for support vector machines to perform very well is they allow misclassifications and can very well handle outliers and allow overlapping classifications. The authors have divided this project into three stages: feature selection and preprocessing, model training and evaluation, where they have used around 5000 images to be trained before preprocessing using image processing techniques. The model has performed very well, and it has yielded around 91.7 percentage and a precision of 90% with the recall of 93.5%, which gives it an upper hand among other high-level algorithms. In order to evaluate the model, they have used 10-fold cross validation along with evaluation metrics such as precision and recall. It is to be noted that this model has performed eight times faster than any deep learning algorithm over there, which takes around 0.18 seconds for one classification, whereas this particular model has taken only 0.025 seconds. For to classify the person with/without a face mask.

Face masks have become a mandatory precaution in most of the countries in the past three years with the rise of Corona virus cases. The government and private institutions across the globe have been striving to invent a vaccine in order to solve these ever-increasing deadly virus cases. Parallelly to this, many institutions have incorporated manual checking of whether the person is wearing a face mask or not at the start of the pandemic. But as the years progressed, people have come up with a solution of automatically identifying whether the person is wearing a face mask or not. A. Das et al.[8] discussed such techniques using TensorFlow, Keras, OpenCV, and scikit-learn libraries in order to identify and alert the institution administrators if a person is not wearing a mask. The authors have used two different kinds of data sets to test on and some basic image processing techniques, followed by training the model by using convolutional neural networks. The model has been trained on 20 epochs, attaining an accuracy of 95.77% and 94.58%, respectively, on two different kinds of datasets. Neural network parameters have been optimised in order to improve the testing accuracy and to avoid overfitting.

Goyal et al.[9] have introduced a novel approach to classifying the people who are wearing masks and who are not. This paper comprises using Convolutional Neural Networks as the backbone to create many layers. Along with Convolutional Neural Networks, the authors have also used OpenCV, Keras, and StreamLit Front End libraries to work on the project. Two models have been created, one for identifying the face in the frame and one for detecting whether the person is wearing the mask or not. Both models have shown compromising results of giving more than 90% accuracy and showing better performance compared to other popular transfer learning algorithms such as DenseNet-121, Mobile Net, VGG-19, and Inception-V3. Moreover, the authors have also proposed measuring the distance between the people and alerting to maintain social distancing along with identifying persons who are not wearing masks properly. Chandan et al.[10] developed a face mask identification system using machine learning approaches, highlighting the significance of modifying current models for realistic applications. A dataset and application for face mask detection were presented by Matthias et al.[11], providing important resources for further study.

Verma et al.[12] presented an automated system using transfer learning-based neural networks, highlighting its effectiveness in preventing viral infections. Asif et al.[13] and S. S. Palani et al.[14] both explored real-time face mask detection systems utilising transfer learning. Asif et al.[13] integrated machine learning methods to enhance detection during the pandemic, while Palani et al.[14] focused on deep transfer learning and fine-tuning techniques to improve detection accuracy. Chowdary et al.[15] also contributed to this area by applying transfer learning with InceptionV3 for face mask detection, demonstrating the flexibility and efficacy of transfer learning models.

Research Gap

Still, there are a number of research gaps in this field, despite the significant advancements made in it. For example, the literature lacks a comparative analysis of several face mask detection techniques. Including transfer learning models, soft-margin support vector machines, and one-and two-stage detectors, among others, different strategies were proposed. However, in-depth analysis on the merits and demerits of each strategy has not been addressed. There is confusion regarding which approaches are most appropriate for different real-world applications due to the dearth of comparison studies.

Furthermore, the majority of research ignored the real-time efficiency in a variety of contexts in favour of developing and implementing detection systems. Further research is necessary to address the difficulty of designing face mask recognition systems to function effectively and quickly in a variety of scenarios, including crowded public venues, healthcare locations, and dimly illuminated areas. For detection systems to be used in real-world scenarios, it is essential that they function dependably in various environments.

Additionally, the research done so far mainly focused on detecting whether the person is wearing a mask or not. But the system is not focused on what has to be done if a person is detected with 'No Mask'. This clearly shows the need for an alerting system to be implemented to warn the authorities when people are identified with 'No Mask'. Making sure that detecting systems can continue to function and be effective over an extended period of time has received less attention than the short-term effectiveness that is the subject of many current investigations.

Various actions needs to be implemented in order to address these gaps. At first, a complete comparative analysis need to be done on existing face mask detection techniques, which will help in identifying the most roaring and high-octane approaches. This provides a chance for the academics and professionals to opt for the correct method to implement in numerous contexts. Second, the primary goal of future research should be developing real-time detection and alerting systems for various contexts.

We may increase the practical use of these technologies and make sure they continue to function well under a variety of circumstances by optimising them for various settings in order to develop more robust detection systems that can adjust to shifting environmental conditions and public health demands. To improve the detecting technologies and make them practicable for daily usage, pilot projects and in-field testing will be a must.

Finally, future research should place a high priority on incorporating face mask detection technology into a larger public health infrastructure. Through partnerships with governmental organisations, medical facilities, and tech firms, scientists can investigate how to integrate detection technologies into currently running public health monitoring programs. The effectiveness of public health initiatives will increase as a result of this integration, which will also produce a more integrated strategy for pandemic management.

2 Methodology

The proposed methodology is innovative in that it combines real-time alerting features with transfer learning to optimise face mask detection across various conditions. The method effectively extracts features from the photos by utilising pre-trained convolutional neural networks (CNNs), specifically MobileNetV2, which reduces the computational load in comparison to training from scratch. A targeted collection of photos with both masked and unmasked faces is used to fine-tune the CNN model, improving the system's ability to recognise face mask usage.

2.1 Workflow of Proposed Methodology

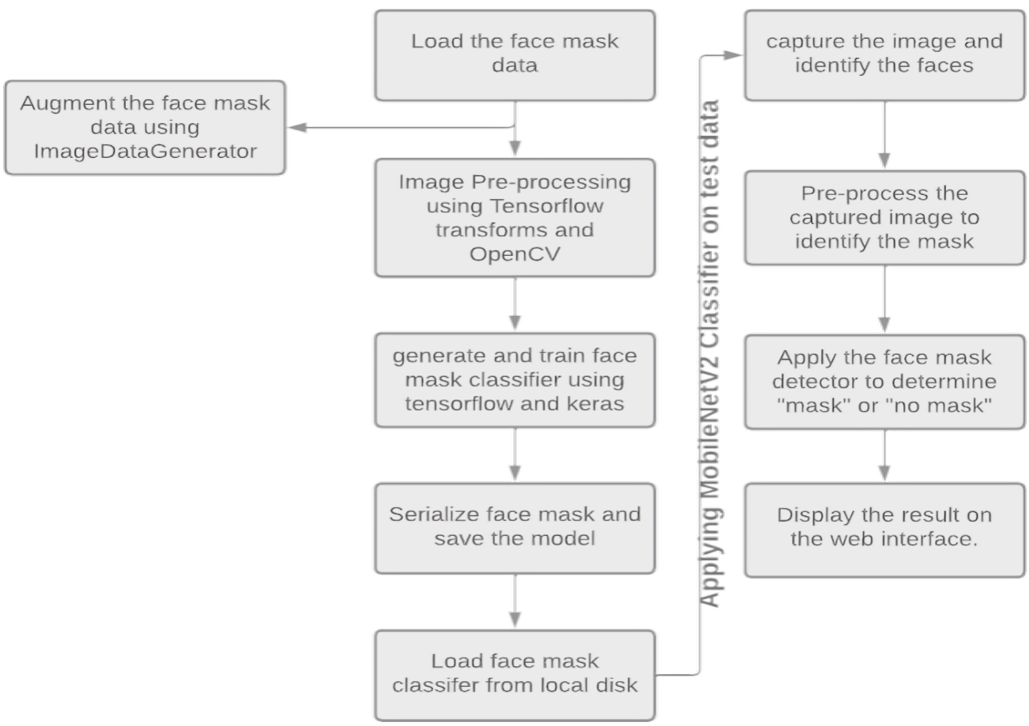

Fig 1. Workflow Architecture

The workflow architecture gives a brief overview of project life-cycle and stages involved in executing the code step by step.

Step_1 Load the dataset and preprocess the images using img_to_array and preprocess_input.

Step_2 Append data and labels into two separate lists.

Step_3 Preprocess the labels using LabelBinarizer() and to_categorical().

Step_4 train_test_split the data before training the model in order to validate the model accuracy by testing it on test data.

Step_5 Using ImageDataGenerator() in order to bring variety and volume while training the data, so that the model can learn different sets of images.

Step_6 Loading the MobileNetV2 Classifier, performing training on the augmented data and saving the model in local file as. HDF5 format.

Step_7 Constructing appropriate graphs in order to validate how good the model is performing.

Step_8 Load the face mask classifier from the local disk and run the web framework.

Step_9 Once the model is loaded, along with the web framework, the webcam automatically opens and tries to identify if there are any faces in the frame. If there are any faces, the model will capture the image and applies image transformations in order to identify the face mask.

Step_10 After image preprocessing is done on the captured image, face mask detector model is applied on top of it in order to detect the person is wearing a mask or not.

Step_11 According to the model predictions, bounding box transformations are applied on the persons face. If the person is wearing a mask, green bounding box is draw, else red bounding box is drawn, along with the confidence percentage.

Step_12 Everything mentioned above is done in a flask web framework, which can also be deployed further in future, allowing the users and authorities to ease the use of computational capabilities and limited memory usage.

2.2 Algorithm Description And Libraries

2.2.1 Transfer Learning

Zhuang F et al. [16] used the transfer learningtechnique, which allows the user to train his or her data set on pre-trained weights that have been trained on millions of Images. Transfer learning algorithms are mostly used for classification tasks such as classifying flower types, animals, handwritten digits, etc. Transfer learning also allows the user to reduce the computational capability and time efficiency, which makes it possible for a better model. Since the traditional deep learning models consist of millions of parameters when the layers are increased, time by time, transfer learning can be a better option in order to reduce training time and get better accuracy by training our own dataset on top of the existing trained parameters. Transfer learning is mostly used in the field of medicine, where data availability might be a big constraint. Due to which various CNN models that have been trained on different types of huge data sets, such as ImageNet and Coco, are used as a building block to work on our own dataset. Some of the popular transfer learning algorithms available right now are VGG-16, VGG-19 Resnet 50, Inception, and MobileNet. All of these algorithms are constantly being monitored and updated, more frequently introducing their own new versions with added layers and improved parameter optimisation. Transfer learning can also be applied to natural language processing, whereas we can use the pre-trained models such as Bert, GPT, and XLNet. Leverage the knowledge of vocabulary, semantics, grammar, and structure of the source task and use those features on our own dataset. This can be a great starting point, which will reduce a lot of computational capability and give better results. Rather than training the entire network from scratch. Not only to classification and natural language processing transfer learning can also be applied to reinforcement learning. To summarise, transfer learning is a powerful technique that has grown in popularity in AI research due to its ability to reduce the amount of labelled data required for training, improve model generalisation, and accelerate training. Transfer learning can be used in a variety of ways, depending on the nature of the source and target tasks, to achieve cutting-edge performance in a wide variety of applications. Transfer learning is likely to play an increasingly important role in enabling machines to learn from experience and perform complex tasks as AI evolves.

2.2.2 MobileNetV2

MobileNetV2 is an efficient convolutional neural network model that is typically designed for mobile and embedded devices. MobileNetV2 was introduced as a successor to MobileNetV1, in order to improve the accuracy and speed of the mobile networks while maintaining their low computational requirements. MobileNetV2 has been trained on the Imagine dataset, which consists of over 1,000,000 labelled images. MobileNetV2 can be used as a transfer learning technique, where the already trained model is used as a feature extractor in order to extract the high-level features, and these pre-trained weights can then be used onto our own data set, which is known as fine tuning, which allows MobileNetV2 weights to adapt to their new task while retaining the knowledge learnt from the ImageNet. One of the main Advantages of MobileNetV2 is its high efficiency in terms of computational capability and memory usage. Additional to that is its ability to perform very well and give higher accuracy on tasks such as classification, object detection, and semantic segmentation. This is the reason why it will make an attractive choice for the developers who are working on medical imaging and autonomous driving. It is an appealing choice for numerous practical applications due to its high efficiency, performance, and wide availability, and it is likely to remain a popular choice for transfer learning in the future. The use of a novel block structure known as ”Inverted Residuals with Linear Bottlenecks” is a key feature of MobileNetV2. This block structure is supposed to increase the network's efficiency and accuracy by reducing the number of parameters and operations needed. Each block has three layers: one 1x1 convolutional layer, one depth-wise separable convolutional layer, and another 1x1 convolutional layer. The first layer reduces the dimensionality of the input tensor, and the second layer performs the actual convolution. A depth-wise convolution applies a different filter to each input channel in this layer, and a point-wise convolution combines the outputs of the depth-wise convolution into a single output tensor. The third layer is used to add more dimensions to the output tensor. The ”linear bottleneck” layer is used to minimise the number of channels in the network so that it achieves higher efficiency without sacrificing accuracy. MobileNetV2 admits additional features that are designed to improve its efficiency and accuracy in addition to the block structure. For example, in order to increase the network capacity for task adaptation, it uses a method known as ”shuffle net” to improve the performance of depth-wise convolutions and integrates a method known as ”SENet.”.

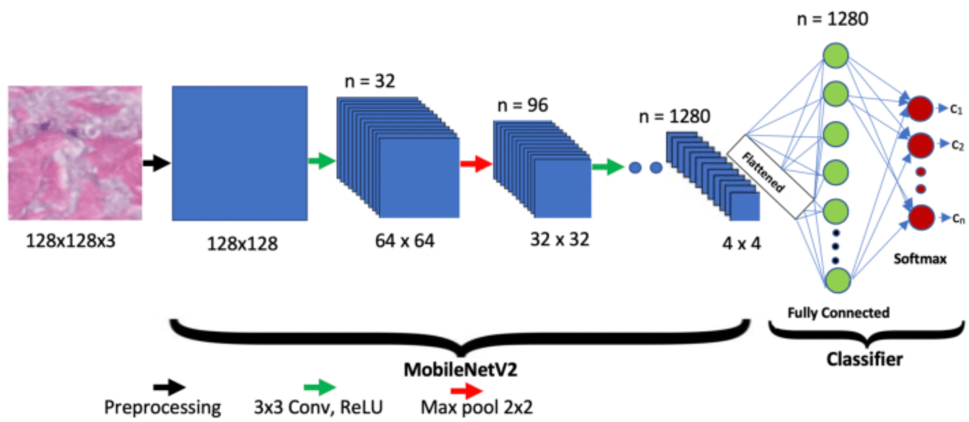

Fig 2. MobileNetV2 Network Architecture TensorFlow

TensorFlow is a library that was developed by Google to ease machine learning and artificial intelligence workflows. This library consists of various functions and methods, which allow the user to construct and deploy any machine learning and deep learning models. TensorFlow, along with the Keras API, works as a base library to work with any deep learning model. Because of its popularity and robustness, TensorFlow has become a must-have tool for data scientists and developers working on machine learning applications.

2.2.3 Scikit-learn

Scikit-learn is a machine learning library that allows the users to work on any machine learning related applications easily and efficiently. It is built on top of Numpy, MatPlotlib, and SciPy. It consists of a wide range of machine learning algorithms for both supervised and unsupervised learning, along with various preprocessing utilities that can be used by the users to clean and transform the data before training and evaluating the model.

2.2.4 Flask

Flask is a lightweight web application framework written in Python that allows the user to integrate their front-end code and deploy their small-scale projects to a website. It is simple to use, flexible, and an ideal choice for many small-scale projects or college-level projects. It is built on the WSGI toolkit, which enables the developers to use a variety of templates and tools to define routes, handle HTTP requests, and create custom views. Flask also supports a variety of extensions that can be used to extend the framework's functionality, such as database integration, authentication, and security features. Unlike other web frameworks such as Django, which are very complex and difficult to learn, Flask gives us an alternative to ease the process and enable the developers to modify the framework to their specific needs. In contrast, Flask is a strong and adaptable web application framework that has gained popularity among programmers working on a variety of projects. Small to medium-sized projects benefit greatly from its simplicity, usability, and flexibility, while larger, more complex applications can also benefit from its wide range of extensions and customisation options.

2.3 Dataset Description

The data set used in the proposed method has been taken from the Kaggle repository. The face mask detection data set(https://www.kaggle.com/datasets/ashishjangra27/face-mask-12k-images-dataset) consists of around 12,000 images split into train, test, and validation data folders. The raw images have been scrapped from Google, and they've been separated, with and without masks, into separate data folders. Each image is of a different dimension, and since any machine learning or deep learning model requires the data to be consistent with the same format, a lot of data preprocessing was required in order to make it trainable data. Data augmentation using ImageDataGenerator has been applied to bring variety in order to make a model to learn different types of image structures and formats in any given condition.

Fig 3. Man without mask

Fig 4. Lady with mask

The system exhibits superior performance in real-time mask detection over conventional algorithms, with improved accuracy. Utilization of an extremely mobile, and device-targeted model such as MobileNetV2 further boosts performance at the very high level in terms of memory use and a computational burden. The system's alarm mechanisms and real-time capabilities also offer useful features that make it an effective instrument for enforcing health compliance.

Metrics like accuracy, speed, and computational efficiency were used to compare the modified MobileNetV2 model to the conventional standards. ResNet and VGG were significantly outperformed by MobileNetV2. The proposed method shows that transfer learning can be adapted in a way for public health applications to achieve practical solutions with better performance and higher scale.

3 Results and Discussion

The proposed method needs to be differentiated from and aligned with conventional approaches in the literature. In order to gain a better understanding of the proposed model effectiveness and strengths, evaluating its performance in relation to previous findings is necessary.

Fig 5. Proposed model identifying the lady with mask on the screen and highlighting the findings by green bounding box

Fig 6. Proposed model identifying the lady without mask on the screen and highlighting the findings by red bounding box

Fig 7. Proposed model identifying 2 people staring at the screen, of which one is wearing a mask and highlighted by green color and the other with red color who is not wearing a mask

An alerting system is implemented byPlaying a recorded alert sound using the Python audio package pygame when someone is identified without a mask.

3.1 Favoring current findings

Table 1 shows the proposed method results in comparison with the conventional methods findings. The comparison takes into account important criteria such as computing efficiency, speed, accuracy, and quantity of the dataset.

3.1.1 Performance in Detection Accuracy

Convolutional neural networks (CNNs) and transfer learning techniques have been used in numerous prior studies, including those by Shilpa Sethi et al.[5] and Das et al.[8], to show high accuracy in face mask detection. By combining bounding box

Table 1. Evaluation metrics comparison of various algorithms

Study		Accuracy	Speed	Dataset Size	Computational Efficiency
Shilpa Sethi et al. [5]	ResNet-50 with bounding box transformation	98.2%	Slow	Large (several thousand images)	High accuracy, but resource-intensive.
Mohammed et al. [6]	YOLO, Fast R-CNN, Mask R-CNN	High detection accuracy	Moderate to slow	Various datasets	Good detection, but complex and slower.
Utomo et al. [7]	Soft margin SVM	91.7%	Very fast (0.025 seconds per classification)	5000 images	Very efficient in computation, but slightly lower accuracy.
Das et al. [8]	CNN with TensorFlow, Keras, OpenCV	95.77% and 94.58%	Moderate	Medium (two datasets)	Balanced accuracy and computational load.
Goyal et al. [9]	CNN with OpenCV, Keras, and Streamlit	>90%	Moderate	Medium dataset	Balanced, good performance, but not as resource-efficient.
Pandiyan P et al. [17]	YOLO v4, tiny YOLO v4, YOLO v5	YOLO v5-88%	YOLO v5- 0.0316	Medium (7959 images)	Balanced speed and accuracy.
Mustapha, M.F et al. [18]	MobileNetv2 Transfer learning	92%	slow	Medium(Two datasets)	Balanced speed and accuracy.
Dodda, R. et al. [19]	CNN with TensorFlow, Keras	>90%	slow	Not mentioned	It was developed and trained on Google colab,leveraging cloud based resources to eliminate need of extensive local hardware.
Prateep, V. et al. [20]	CNN	99.2%	Not mentioned	Not mentioned	Balanced accuracy and computational load.
Proposed method (MobileNetV2)	Transfer learning with MobileNetV2 and real-time alerting	~95%	Very fast (optimized for real-time detection)	Large, diverse dataset	High efficiency, optimal for real-time applications

modifications with ResNet-50, Shilpa Sethi et al. [5] were able to attain an accuracy of 98.2%. Das et al. [8] also reported 95.77% and 94.58% accuracy rates with CNN-based models. These results are supported by the current model, which makes use of MobileNetV2, which offers comparable or even better accuracy while preserving computing efficiency. This proves that the current method can compete with other top-performing models, proving that transfer learning works well for facial mask recognition.

3.1.2 Real-time skills

The proposed model's alerting system and detection techniques align with the goals of earlier studies. Utomo et al. [7] demonstrated the benefits of employing a soft-margin support vector machine, attaining a processing time of 0.025 seconds for each classification. The proposed model, which is improved with MobileNetV2, prioritizes speed as well, which makes it appropriate for real-time applications in busy contexts and validates the results of previous studies.

3.1.3 Adaptability and Generalisation

one of the main contributions of the proposed work is it's ability to adjust to different situations. This emphasis on venerability is in line with the findings of Zhuang et al. [4], who emphasized the value of transfer learning in enhancing model performance in a variety of contexts. Building upon previous research, the current study fine-tunes MobileNetV2 for several scenarios, guaranteeing that the model stays effective in recognising face masks under varying conditions. This helps to validate the findings.

3.2 Conflicting with Recent Research

3.2.1 Trade-off Between Speed and Accuracy

Shilpa Sethi et al.[5], used more sophisticated models, such as ResNet-50, to obtain great accuracy, but at the expense of computational efficiency and speed. However, the current study supports a model (MobileNetV2) that prioritizes real-time performance and is tailored for mobile and embedded applications. Although this option uses more resources and has a little lower accuracy than more complicated models, it has major benefits in terms of speed and efficiency. This trade-off could go against results that place the highest value on accuracy, showing that the choice of model is highly dependent on the particular application and its limitations.

3.2.2 Size and Diversity of the dataset

Although the dataset utilized in this work is vast and diverse, it may not be the same as those used in other studies. For example, Das et al.[8]'s dataset required substantial preparation and training on two separate sets of data. Studies that concentrate on highly specialized datasets designed for certain situations may be contradicted by these differences in dataset properties, which could also result in discrepancies in model performance. The focus on venerability in this study may lead to a less specialized but more general model, which may cause disagreements with models that are optimised for specific datasets.

3.3 Comparison with Current Reports and Discussions

3.3.1 Compared to Other Architectures, MobileNetV2

The use of MobileNetV2 in this study was contrasted with other widely used architectures, including ResNet, VGG, and Inception. Prior studies have shown that ResNet and VGG are computationally demanding, despite their higher accuracy. MobileNetV2, on the other hand, better balances computing efficiency and accuracy, which makes it more appropriate for real-time applications. This comparison demonstrates why MobileNetV2 is the best option in situations where scalability and speed are essential.

3.3.2 Integration of Transfer Learning

Asif et al.[13] and Chowdary et al.[15] proved transfer learning's efficacy in increasing detection accuracy. The utilization of pre-trained MobileNetV2 in the proposed model serves to further emphasize the importance of transfer learning, especially in situations where a substantial quantity of labelled data is not easily accessible.

3.3.3 Integration of Alerting System

The novelty of the proposed system is in the implementation of a sound system. A recorded voice message is played by using Python audio package 'pygame' when a person is detected with 'No Mask', so that concerned authorities will react and instruct the persons to wear a mask.

4 Conclusion

The proposed model, with the use of MobileNetv2 together with a combination of transfer learning, achieves an accuracy of 95% and outperforms the conventional approaches in terms of speed, accuracy, and adaptability. It does, however, also offer a different trade-off between detection accuracy and computational efficiency from slower but more complicated models. The novelty of the proposed method is in the implementation of an alerting system to alert the authorities when a person is identified with 'No Mask'. Though it does sacrifice some accuracy for speed, the model's merits are in its real-time capabilities, flexibility to various conditions, and scalability for resource-constrained contexts. These results add important context to the ongoing development of face mask recognition technologies and showcase the importance of selecting the suitable model depending on the particular application. Future enhancements may include fine tuning the equilibrium between speed and precision, broadening the variety of datasets, and examining the model's efficiency in different scenarios, like incorrect mask application.

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