Face Mask Detection System for Safety Assurance in Nuclear Power Facilities from Harmful and Hazardous Substance using Convolutional Neural Network and Image Processing

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ABSTRACT
This research develops a computer vision-based system to detect face masks in nuclear power plants, ensuring compliance with safety regulations . The system employs image processing techniques to enhance and preprocess images from surveillance cameras, which are then fed into a Convolutional Neural Network (CNN) model for classification . The CNN model is trained on a large dataset of images collected from various power plant scenarios, achieving high accuracy in detecting individuals with or without face masks . The system detects mask-wearing individuals in real-time, enabling prompt action to ensure personnel safety and compliance . This automated system reduces manual monitoring efforts, enhances overall safety, and supports compliance with regulations . The proposed system demonstrates the effectiveness of CNN-based image processing in face mask detection, offering a reliable solution for nuclear power plants and potential applications in other industries .

General Terms
Face Mask Detection

Keywords
Face Mask Detection ,Nuclear Power Plant,Image Processing, Convolutional Neural Network,Safety Compliance,Automated Monitoring .

1. INTRODUCTION
Nuclear power plants are regulated very strictly and for ensuring the safety of all personnel whether it meant professionals or plant workers the use of face masks is a top measure[1]. The task of providing every employee with face masks in the required areas is crucial, especially in high-risk zones. But the process of manual monitoring is slow, inaccurate, and does not provide a quick response. The recent developments in computer vision and deep learning give the opportunity to have a proper solution for automation of face mask detection. With the help of image processing, it becomes possible to retrieve the crucial features from the images and to apply Convolutional Neural Networks (CNNs) in classifying the individuals as if they were wearing a mask or not. This study mentions an alternative method in identifying face masks in nuclear power plants with the use of image processing and CNN-based classification[2]. It gives an image to the idea of real-time detection, making it possible for taking immediate measures to sustain the standards of safety. The system is empowered by CNNs, so they can recognize the face masks that people wear in different conditions, such as different lightings, angles, and occlusions, accurately. That way this system would perform better with respect to safety augmentation, efficient tracking of manual activities, and valid support of regulations in the nuclear power plants. Further, this study addresses the issue of computer vision based developments in industrial safety applications, shedding light on the use of CNNs in the detection of face masks.

2. LITERATURE SURVEY
[3] Paper use library like TensorFlow ,Keras, and OpenCV for the real-time face mask detection and CMNV2 model for photo and video which gives the result of 99.64% with the error rate of 0.36% for with mask and without mask by using 1376 JPEG and PNG images from Prajna Bhandary dataset which is collected form Gitub . The model give less accuracy if there is some sudden facial movement in real time video and the prediction calculator shows the value of false positive is zero.

[4] Author use transfer learning of MobileNetV2 to build the framework for a robust model for face mask and untargeted FGSM adversarial attack on face mask detection by the help of sophisticated face mask dataset having 14535 images which further divided into two parts like FMS and MMD for training and testing respectively . Model gives the accuracy of 95.83% where it drops from 95.83% to 14.53% if there is the FGSM attack . Bias towards Chinese face and limited images in the dataset found and they act like drawbacks.

[5] Gives the description of the model says that fine tuned MobileNetv2 is used for classification where single-shot multi-box detector used for face detection . this model is a combination of trained VGG-16, RestNet-50 and MobileNetV2 and it deals with efficient face mask dataset contain 14535 images achiving a good accuracy for both training and testing respectively . Limited FPS on CPU for the MobileNetV2 considered as a drawback for the model .

[6] Presented deep learning techniques like CNN , AI , and YOLOV3 are used for face mask detection which works on a dataset contain 67705 images gives the accuracy of 98.9% and 98.74% for training and testing scenario respectively. On the other hand model shows the accuracy for single person in day time is 99% where as it decrease to 74% for multiple persons in night time . Partially hidden face create issue in detection and also the system needed high quality camera for recognition .

[7] Implement the model which contains 2 stage CNN architecture , modified centroid tracking and object tracking algorithms for stable detection in video stream with the help of CCTV camera . Dataset by Larxel collected from Kaggle resulting highly accurate FMDS with multiple faces are various angles . The detection algorithms may fail due to noise and blur motion .

[8] Algorithms like Fast RCBN , Faster RCNN , YOLO and SSD are used to detect the face mask and deep learning and computer vision used to detect the object with CUDA technology on the GPU execute on the dataset of 3694 images gives the accuracy of 97% after 20000 epochs . Solution may be long due to every field prediction .

[9] The main focus was on developing a convolutional neural network model and further combined it with data augmentation tricks followed by MobileNetV2First step involved collecting a dataset of the public images, and then image pre-processing was carried out. After that, CNN did real-time classification if people are wearing masks through the video streams or not .The data augmentation techniques was seen as ways of enriching the dataset for rigorous model training, therefore improving performance in mask detection. Upon using MobileNetV2 the results were more efficient then the conventional methods due to demonstration of more number of true positive rate indicating its credibility in accurately detecting use of masks in different scenarios. This study further aims to work on enhanced image segmentation techniques .

[10] The authors demonstrated the increasing requirement of face mask usage due to presence of COVID-19 pandemic highlighting the limitations of monitoring compliance in public places .The model proposed by them comprises of machine learning algorithms and image processing techniques for detection of individuals with masks and without masks, incorporating deep learning .MobileNetV2 classifier which yielded high accuracy .It was trained on augmented datasets and had an accuracy of 97.86% with respect to the training set and 99.22% with respect to the test set. It is quite effective at discriminating among class decisions on a given person in the data .The system could identify masks in images containing several faces with different direction which showcases a robustness and practical relevance of the framework.

[11] The paper demonstrates a deep learning model such as Inception V3 which was fine tuned and trained on the image dataset consisting of 1570 images . Out of which 70% of the images were used for training and 30 % of the images were used for testing purpose. The experiment was carried out using Google Colab . Image augmentation was performed so as to increase the diversity of the dataset by performing distinct operations .The images were sheared , contrasted ,horizontally flipped, rotated ,zoomed and then images were blurred and whole dataset was rescaled to 224*224 pixels further transformed to a gray-scale representation .It yielded an accuracy of 99.9%.

[12] The authors carried out the study focusing on the image processing techniques such as grayscale conversion which was employed .Feature extraction and convolutional neural network were used for classification and detection of a person with mask or without mask .The steps followed for the study includes preprocessing of the images then comes the cropping of the images finally carrying out the classification of the dataset .Total of 690 images with mask and 686 images without mask was used .Here the convolutional layers were compacted into a single block furthering the process of classification .The model generated an accuracy of 0.98 and encompassing loss of 0.085 and is less complex in nature other than the existing models.

3. DATASET

Face mask detection dataset in nuclear power plants collected data from "Face Mask Detection Dataset" via Kaggle which consists of a total of 7553 images. These are split into two primary groups - 3725 pictures showing masked people and 3825 images of people without the mask[13]. This dataset is important for the practicing and testing of machine learning models programmed to find the occurrence or vice versa of face masks in different areas of nuclear power plants. The equal representation of images with and without masks guarantees that the model will be taught to efficiently recognize these two groups. Usage of this dataset the creation of technology like masks that can be used to plan computer vision systems that can check the presence or absence of masks right at high risk places such as nuclear facilities. The primary step to the development of mask detecting mechanisms is the collecting of data from scratch on-site by skilled professionals who then manually encode through the collected data to feed into the systems. The face mask detection system can assure compliance with these standards. Following the innovative relation of computer vision and AI, datasets of this kind drive the technology that ensures the safety of workers and the productivity of the infrastructure.

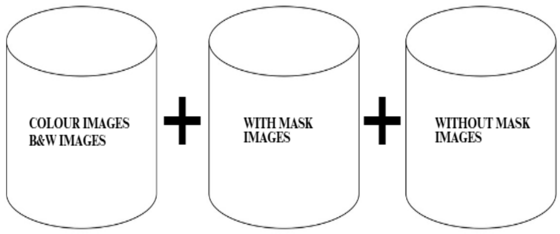

Fig 1 : Dataset with All it's Attributes

3.1 Image With Mask

Following the extraction of the dataset for the face mask detection in the nuclear power plants, the "with mask" category is made up of 3725 images. Pictures of the individuals show them wearing different kinds of face masks such as surgical masks, N95 respirators, and cloth masks. While the pictures introduce different individuals and situations that this would not actually happen, each image comes with various dimensions, poses, and background of the image so as the model is made sure for the recognition of the presence of masks at various sites within the nuclear facility. Specifically, this portion of the data set is the 11 most important part of the training machine learning algorithms to correctly identify and classify the cases where the personnel are complying with the necessary safety protocols through the use of a face shield.

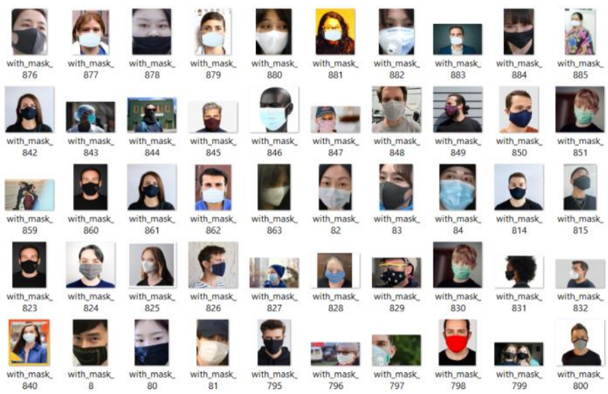

Fig 2 : Image With Mask

3.2 Image Without Mask

In the case of the "without mask" category, this dataset contains 3825 images of people with no sort of face covering across nuclear power plant settings. These images differ with respect to environmental settings and backgrounds to ensure all-inclusive training data for the machine learning model. The recognition of the instances when persons are not following the safety protocols is very important so as to ensure strict adherence to safety rules within nuclear facilities. This subset of the dataset provides a way for 12 models to accurately detect and flag instances of non-compliance with face mask regulations, ensuring high safety with reduced risks of exposure to hazardous materials.

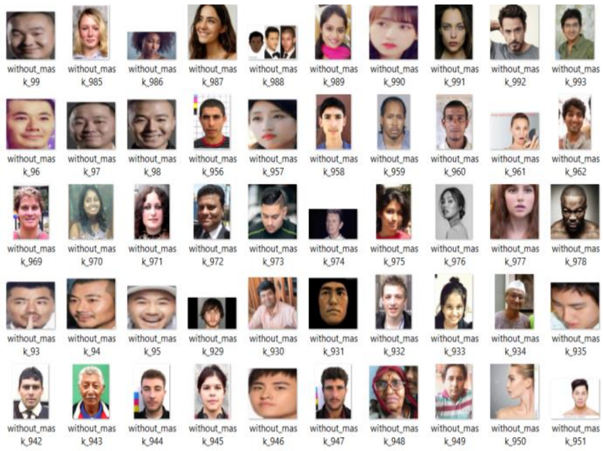

Fig 3 : Image Without Mask

4. PRE-PROCESSING METHODS

Pre-processing images plays a key role in image analysis. It boosts image quality and readies pictures for deeper study. This step uses many methods to change raw images into forms ready for feature finding and object spotting. The process involves resizing, normalizing adding variety to data, filtering, setting thresholds, and finding edges. These tricks cut down noise, fix biases, add more types of images, and make important parts stand out. When we prep images this way, our analysis models work better and make fewer mistakes. We can learn more from the pictures too. Good pre-processing matters a lot in things like face ID finding objects medical scans, and quality checks - areas where getting image analysis right counts. By fixing up images first, we tap into all the good stuff hidden in picture data and get way better results .In this paper we use mainly three types of pre processing methods as follows :

4.1 Image Resizing

It is the process of resizing the dimensions of all the images to a preset dimension that the CNN model is expecting. Usually, the input image is expected by the CNN model to have both the height and the width to be the same or example, a size like 224 x 224 pixels is placed in most popular CNN structures, such as VGG, ResNet, MobileNet. Image resizing sets the dimensions of input images within the face mask detection working with CNN in the nuclear power plant and, in a way, streamlines preprocessing. This ensures that there is uniformity in the dimensions of input images across the dataset, hence easy processing by the convolutional layers within the CNN.

4.2 RGB Image Conversion

Face mask detection in nuclear power plants relies on image processing and CNN models. RGB 14 conversion plays a key role in getting images ready for the CNN. This step changes the original image format into something the CNN can work with more . It's like translating the picture into a language the computer understands better. This conversion has a big impact on how well the system can spot face masks.

4.3 RGB Image To Numpy Array

One of the most common image pre-processing techniques is converting RGB images to NumPy arrays. The term "conversion" technically means conversion of the pixel values in an image from a scale of values going from 0 to 255 to a normalized scale, like going from 0 to 1, which might be used during numerical computations. An RGB image is represented as a 3D NumPy array, every pixel being a 3-element vector containing the intensities of red, green, and blue. This conversion helps to do computational image processing and analysis with strong numerical libraries such as NumPy and SciPy. The output array can be used in various preprocessing techniques, from normalization and data augmentation to feature extraction, thus providing it as a very important step in the computer vision pipeline to support image analysis, object detection, and, most importantly, efficient and accurate machine learning model training. Converting the images from RGB to NumPy arrays opens their power for the purpose of using numerical computing in the ostensible fields of the image. In summary, application of these preprocessing techniques with care enables a strong face mask detection system.

5. BASE MODEL ARCHETECTURE

A Convolutional Neural Network (CNN) is a deep learning model designed for image analysis. It utilizes convolutional layers to extract spatial features, pooling layers to reduce dimensionality, and fully connected layers for classification. This architecture efficiently learns complex patterns, making CNNs powerful for tasks like image recognition and object detection.

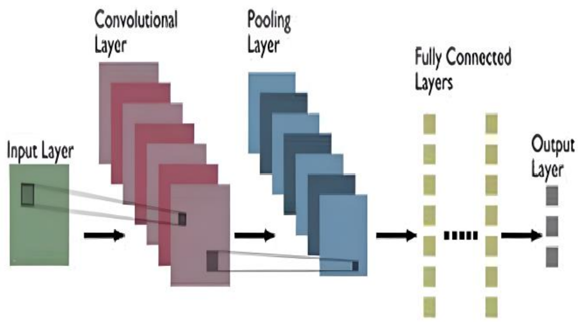

Fig 4 : CNN Model with it's Layers

6. PREDICTION WORK FLOW

Prediction of face mask detection with a Convolutional Neural Network involves a workflow that starts first by taking an image of the user. The user can upload a photo or capture one automatically through a camera of a device. Then, the following pre-processing step is done to get the image ready for analysis. The first step is to resize the image to the same dimension a dimension expected as an input in the CNN model, often 224x224 pixels. Resizing helps to maintain uniformity in the image and reduces the computational load. After resizing, the image is normalized, correcting in pixel value, to a standardized scale, often between 0 and 1. Normalization helps the fast training and better performance of the model. Other preprocessing steps that can further be added to this include histogram equalization, which enhances contrast, and face alignment, in which all faces are aligned to a single orientation, making it easy to detect the features within the face. After preprocessing, loading the pre-trained CNN model is quite necessary. This is because it has been trained based on a great amount of training data encompassing lots of pictures, majorly of humans, without and with masks. Pre trained models thus enable qualities to detect and classify different facial features and masks according to these common mask attributes. Some of the widely used CNN architectures are VGG16, Rest-Net, or it may also be some special design custom models for the detection of masks. The preprocessed image is fed into the preloaded CNN. On this step, features will be extracted relative to the edges' existence on the image, concerning textures, and patterns in regard to masks. Further, these are processed into pooled layers to reduce in dimension the feature to be kept critical information in it. The fully connected layers at the end of the network utilize these extracted features to classify the input image as containing either a mask or no mask. Generally, there will be a soft-max involved for classification in the output layer. It provides a probability score for each category. For example, if the probability score for the category 'mask' is greater than that for 'no mask', then it makes a prediction that the person is wearing a mask. On the contrary, if the 'no mask' category gets a higher score, then the model gives the result that this person is not wearing a mask. Finally, the prediction result is communicated back to the user by indicating if they are wearing a mask, which can be displayed on a screen or trigger further action, e.g., alert raised in the public health monitoring system. The workflow is then completed as the tracks of the prediction. The automated, effective workflow will ensure that face mask detection is achieved accurately in real-time, saving life daily.

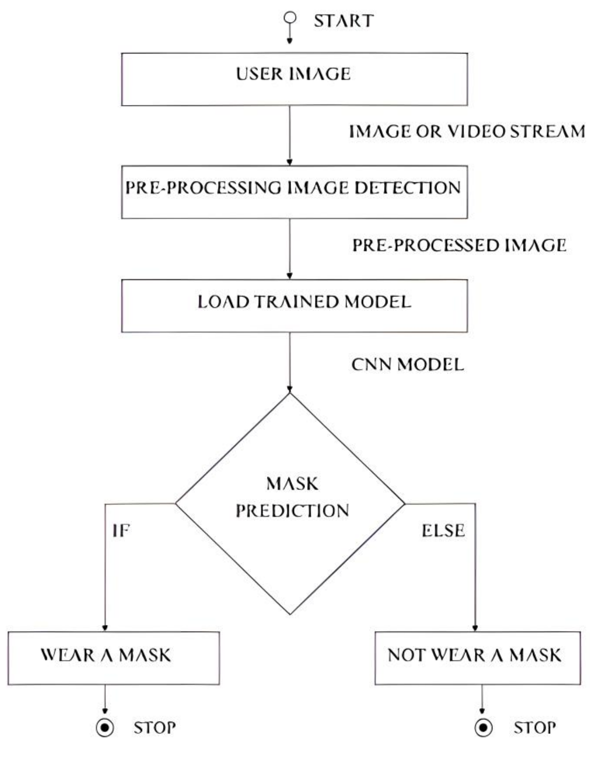

Fig 5 : Prediction Work Flow

The main prediction model works like this and the prediction takes place according to the condition . There are two condition if and else and it predict and then the model will be terminated .

7. IMPLEMENTATION

Concretely, realization of a CNN model for face mask detection in a nuclear power plant involves the following critical implementation steps in preparation to collect a comprehensive data set, which consists of individuals with and without face masks in different lighting conditions and under a good number of angles typical to this environment:. These include resizing of images, normalization of pixel values, and dataset augmentation through the introduction of variations like rotation and flipping prior to augmentation of the model to increase its robustness . The convolutional layers in the model extract important features about an image, like edges and textures, which are relevant in the identification of a face mask. The pooling layers reduce the dimensionality of the features extracted, whilst still retaining the features needed to reduce the computational load statistically. Fully connected layers at their end use the extracted features to classify them. The model is trained using the fed pre-processed images together with their respective labels with cases for both positive and negative instances that is, a labeled dataset of nuclear workers with positive and negative examples of wearing a mask. The model will, therefore, learn to recognize patterns associated with the wearing of face masks through back propagation and optimization algorithms that tend to adjust the weights of the model so as to minimize the classification error. After the model has been trained, it is then deployed in the surveillance system of the nuclear power facility. This system is based on live video feeds or captured imagery processed in real time at the entry point and other critical areas. The processed image is further passed by the trained CNN model, pretested to predict whether a person has a mask or not. If the person is noticed without a mask, appropriate response can be triggered toward security personnel or automated systems, thereby ensuring compliance with safety protocols. Such an implementation would go great ways toward safety enhancement while at the same time meeting the regulatory requirements related to the mask-wearing issues in potentially severe environments, like those in or around nuclear power plants . This proposed model contain five types of layer i.e Conv2D , MaxPooling2d , Flatten , Dense , Dropout . The working principle of each layer are given below.

7.1 Conv2D

For CNNs, the `Conv2D` layer applies learnable filters to images. The filters convolve the input images through sliding, leading to the extraction of spatial features. The dot product between each filter and the local regions mapped to the feature maps captures the patterns at hand, like edges and textures. Activation functions introduce nonlinearities that enhance the complexity of the model. Stride decides how far the filter can move; hence, it affects the output size. Padding adjusts the dimensions of the input 22 in such a way to maintain an equal output size while still having consistent features. Multiple filters apply to a multi-channel input and estimate different feature maps; therefore, the `Conv2D` layers let CNNs curate hierarchical representations, making them vis-à-vis very imperative for high-accuracy tasks in image recognition and object detection.

7.2 MaxPooling2D

For instance, some layers in a CNN are very basic for the processing and transformation of input information into obtaining an accurate classification or detection. MaxPooling2D is one of the pooling layers doing down-sampling by taking the maximum value within each region of the convolutional feature map. This reduces the spatial dimensions of feature maps while retaining only the most important information and hence improving computational efficiency and robust features extraction.

7.3 Flatten
This 2D matrix of feature maps is reshaped into a 1D vector with the help of a Flatten layer, making the data ready to feed into fully connected layers. This finally gives a consolidated form to the spatial information drawn by the previous layers and is fit for classification or regression tasks.

7.4 Dense
These dense layers are also called fully connected layers and are responsible for learning complex relations between the features extracted from the input data. This way, each neuron from the Dense layer is connected with all neurons of the previous layer, allowing all features to be combined and providing a higher abstraction.

7.5 Dropout
Dropout layers are a regularization technique involving the deactivation of a fraction of the neurons in the middle of training. These layers allow for over-fitting prevention by forcing a model to generalize toward the unseen data. This makes the model work with the different dangerous features it has to rely on every time it makes a prediction . These are layers of which any CNN is composed, having hierarchical feature extraction, spatial reduction, and nonlinear transformations that enable a model to learnedly classify patterns of complex data like images with high efficiency, hence ensuring appropriate performance in tasks such as image recognition and object detection.

7.6 Dataset Split and Preparation
The dataset was then divided into 80% for training and 20% for testing. The model will learn from a good part of the dataset during training and will use a reserve, small, and unseen part for checking its 23 performance under training.

7.7 Training Process
The CNN model is trained using the training dataset for 20 epochs. An epoch is the process of passing a batch of the images through the network and updating the model's weights proportional to the error, or loss, which is computed between the expected and the actual outputs. Therefore, the training time for 410 ns results from the sum of all the different compute adjustments and updates over the full training set.

7.8 Testing Process
The testing dataset, considered as part of the validation phase or testing of the architecture, validates the trained model after the completion of training. For this respect, the testing dataset is passed through the trained CNN, and accuracy counting is taken for each set of test images. Beyond this, some total time of 60 ns is taken for testing; this time includes not only the processing of each image through the trained model, but also the final calculation of the accuracy metrics.

7.9 Accuracy Assessment
Hereby, the test accuracy of 93.79% means the model's correctness of prediction for either the presence or absence of face masks, related to the instances from the test dataset, in 93.79% of cases. This metric is quite pivotal because it quantifies the effectiveness of the model in making correct predictions on new data; hence, it generalizes beyond the training dataset .In summary, the training and testing of a CNN for face mask detection using the specified parameters for inputs and results require careful data preparation, iterative training epochs, and rigorous evaluation. The dataset split of 80/20 ensures there will be robust model training and validation. The achieved test accuracy of 93.79% therefore underscores how well the CNN could differentiate between images of masked and unmasked faces. The respective times of 410 ns and 60 ns for training and testing, specifically, reflect the necessary computational efficiency needed by the CNN in processing and analyzing image data for real-time applications. This pervasive measure of model performance underscores the utility the model can have in applications requiring reliability and accuracy in face mask detection as part of a global system of surveillance pertinent to public health and safety monitoring. In that test it show the difference between train loss VS validation loss and train accuracy VS validation accuracy in a graphical manner for better understanding of the model which is given below .

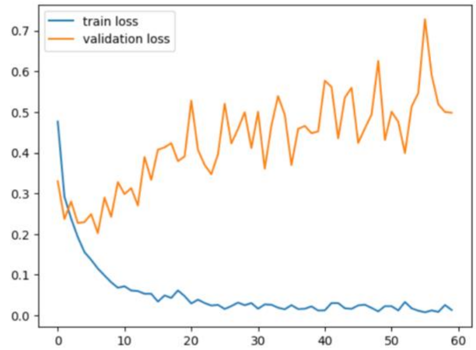

Fig 6 : Train loss VS Validation Loss

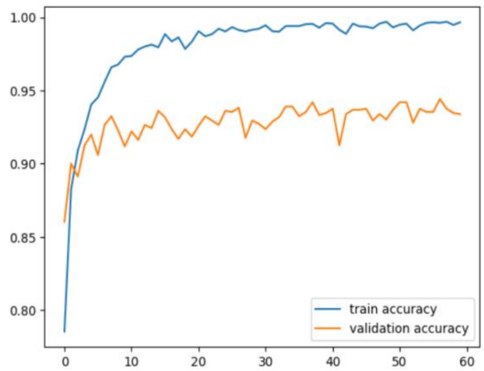

Fig 7 : Train Accuracy VS Validation Accuracy

8. RESULT AND OUTPUT
The test accuracy of the CNN model for face mask gives higher accuracy because the architecture attains 93.79% proving that the model can detect the correct classification among the images either wearing a mask or not. There is very encouraging behavior of the results, even with 60 epochs of training using an 80/20 split dataset; the training time is 410 ns and the test time is 60 ns. Such outputs will be a validation of the effectuality of the CNN in real-time applications and give proof of worth in offering marked potential that will see improvement in the safety protocols in such environments as the health facilities, public spaces, and industrial setups, among others, in which the adoption of the face mask wearing culture seems to be.

Fig 8 : Path Of The Image Will Be Pasted Here

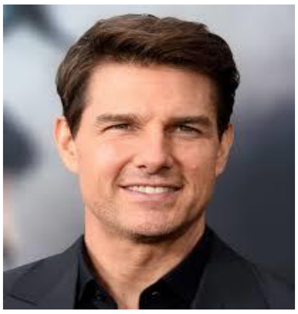

Fig 9: Person Without Mask

Fig 10: Person With Mask

It shows this output where the individuals are wearing mask or not.

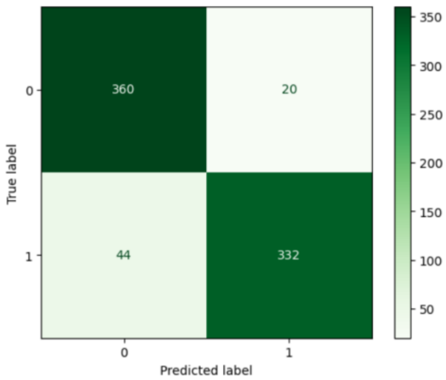

Fig 11: Confusion Matrix Of CNN Model

Table 1. Performance Metrics Of Person With Mask & Without Mask

Model	Precision	Recall	F-1 Score	Accuracy
With mask	95%	90%	92.7%	93.79%
Without mask	90.7%	95%	93.5%	93.79%

9. RESULT COMPARISON

The proposed CNN model attains a testing accuracy of 93.79% in face mask detection. In comparison, the Caffe model and MobileNetV2 has an accuracy of 96.64%, hence outperforming in the detection of masked individuals .CNN and MobileNetV2 attains a good accuracy of 97% during testing and is also much more efficient in processing image data in tasks related to mask detection. At last Fast Neural Network achieve 94% during the testing . Although it is marginally weaker than the benchmarked norm, precision remains robust for the proposed CNN model, and the model is indicated as being able to work in a holistic real-world environment for effective and accurate face mask detection to help in matters of public health control and safety protocols in a wide range of environments.

Table 2. Comparison Table With Other Models

Models	Accuracy
Proposed Model	**93.79%**
Caffe model and MobileNetV2	96.64 %
CNN and MobileNetV2	97 %
Fast Neural Network (FNN)	94 %

Table 3. Comparative Analysis Of Other Datasets

Authors	Dataset Used	Accuracy
Kumar et al. [3]	JPEG images	99.64%
Sheikh et al. [5]	Efficient FMD	97.58%
Ding et al. [8]	Facial Dataset	97%
Proposed Model	**Face Mask Detection Dataset**	**93.79%**

10. CONCLUSION

The previous proposed face mask detection system shows good and effective performance in predicting whether people are wearing a mask. Further dividing the dataset as 80% for training and 20% for testing, the model has been able to reach an increase in its accuracy compared to its initial performance at the 60 epochs during iterative training. This kind of iterative training process ensures that the model is learning and refining through further learning in such a way as to classify the images quite accurately .It is of importance to note that this view might be relative, subject to the processing power of hardware, in terms of time it would take to train and test the model. Here, the times were 410 ns for training and 60 for testing, but one can achieve even less using high-end processors to optimize for real-time applications .The success of the face mask detection model presents the possibility for its utility across scenes that range from healthcare facilities to public places and finally to industries. The system will help public health with infectious disease control by detecting cases where face mask utilization is nonexistent. Compliance behavior insights from the system aid in developing specifically targeted interventions to improve safety measures overall .Increasingly refined training models and hardware will thus enable the improvement of accuracy, speed, and reliability of these face mask detection systems.

11. FUTURE WORK AND LIMITATION

Future work in face mask detection involves the reduction of dataset noise and more refined data collection, thus an increased accuracy. Techniques such as data augmentation through rotations, flipping, and zooming and the use of deeper networks enhance performance. Some ways of improvement in accuracy are high-resolution images and hybrid models, combining the use of CNNs with other methods. On the other hand, the pitfalls of over-fitting and higher computational complexity have to be steered clear of, and the data has to be diverse and representative.

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