Real Time Face Mask Detector

Abstract :-

In this research paper, we present a real-time face mask detector that is developed using machine learning with ml5.js, a web-based machine learning library, making it easily applicable in real-world situations. The detector can accurately identify individuals not wearing masks in real-world scenarios, with an average accuracy of 78.51% across 10 iterations of testing. The model was trained on approximately 850 images of people with and without masks, and tested on approximately 500 images from each category.

During the COVID-19 pandemic, face masks have become a crucial part of maintaining public health. The real-time face mask detector has potential implications for public health and safety by allowing for quick and efficient monitoring of mask-wearing compliance in public spaces. The integration of machine learning with a web-based solution can make it easier to deploy in real-world scenarios. In conclusion, our research provides a promising approach to address the need for mask-wearing compliance and public safety.

Introduction :-

The COVID-19 pandemic has resulted in the widespread use of face masks in public areas, with health organisations and governments recommending or mandating their use as a preventative measure against the spread of the virus. This has created a need for a dependable and effective system to detect whether individuals are wearing face masks. The following breakdown explains why, how, who, when, and where a face mask detection machine learning model is required:

Why: The need for a face mask detection model arises from the COVID-19 pandemic and the importance of face masks as a means of preventing the spread of the virus. By detecting people who are not wearing masks, the system can help to enforce compliance with public health guidelines and reduce the risk of infection. The system can also help to prevent asymptomatic carriers from unknowingly transmitting the virus to others.

How: The face mask detection model works by analysing images of people's faces and determining whether they are wearing face masks. The system can be trained on a dataset of images of faces with and without masks, using machine learning algorithms to classify images and identify patterns. The model can then be integrated with existing security cameras, mobile apps, or web applications to provide real -time detection and alerts.

Who: The need for a face mask detection model is felt by various stakeholders, including governments, businesses, schools, universities, public transportation, and other public places. These organisations can benefit from the system by ensuring that employees, customers, students, and passengers are wearing masks in the workplace, on campus, or during travel. By

implementing a face mask detection system, organisations can take a proactive approach to preventing the spread of infectious diseases and promoting public health.

When: The need for a face mask detection model has arisen during the COVID-19 pandemic and will continue to be relevant even after the pandemic is over. Even as vaccination rates increase and restrictions are lifted, the system can play a key role in preventing the spread of other infectious diseases and ensuring public safety in crowded spaces.

Where: A face mask detection model can be implemented in various locations where face masks are mandatory or recommended, such as workplaces, schools, universities, airports, train stations, public transportation, and shopping centres. By detecting people who are not wearing masks, the system can help to enforce compliance with public health guidelines and reduce the risk of infection in these public spaces.

Due to the COVID-19 pandemic, it has become crucial to monitor mask-wearing compliance in public areas as non-compliance increases the risk of virus transmission. However, manual monitoring can be difficult to implement on a large scale and time-consuming. Therefore, the aim of this project is to develop a machine learning-based real-time face mask detector that can accurately identify individuals not wearing masks in real-world scenarios. The proposed solution will be a web-based application that can be conveniently deployed and used in different public spaces, potentially contributing to the reduction of COVID-19 transmission.

Identification of Task:

- **Data collection**: Gather a dataset of images of faces with and without masks.
- **Data preprocessing**: Process the data to ensure that it is ready for use in training the model.
- **Model training**: Train the model on the dataset using appropriate techniques.
- **Model evaluation**: Evaluate the performance of the model on a separate test dataset to determine its accuracy
- **Model deployment**: Deploy the model in a real-world web-based solution.

Literature Review :-

These papers show that there are a number of different models that can be used to detect face masks in real-time. The best technique for a particular application will depend on a number of factors, such as the accuracy required, the computational resources available, and the type of data that is available.Some of them are listed below :-

- YOLOv3 technique and haar cascading classifier: In the paper "Face Mask Detection on Photo and Real-Time Video Images Using Caffe Framework" [1], the authors used YOLOv3 and haar cascading classifiers to detect facial masks in real-time. They tested their model on both photo and real-time video images and achieved a high accuracy rate of 98.3%.
- Transfer learning with a pre-trained InceptionV3 model: The paper "Face Mask Detection on Photo and Real-Time Video Images Using Caffe Framework" [1] also used transfer learning with a pre-trained InceptionV3 model to detect people with or without masks. The authors fine-tuned the model with a small dataset of masked and unmasked faces and achieved a high accuracy rate of 99.5%.
- Convolutional Neural Network (CNN): In the paper "A real-time face mask detection system using convolutional neural network" [2], the authors used CNN to classify images as "with mask" and "without mask." They used a dataset of masked and unmasked faces to train their model and achieved a high accuracy rate of 96.5% on real-time video images.
- Machine learning using packages like TensorFlow, Keras, OpenCV and Scikit-Learn: In the paper "Face Mask Detection Using Machine Learning" [3], the authors used machine learning algorithms implemented with packages like TensorFlow, Keras, OpenCV, and Scikit-Learn to detect faces and identify if they were wearing a mask or not. They used a dataset of masked and unmasked faces to train their model and achieved an accuracy rate of 94.7%.
- Real-time Mask Detection using a Modified MobileNetV2 Model: The paper "Real-time Mask Detection using a Modified MobileNetV2 Model" [4] proposed a modified version of the MobileNetV2 architecture that achieved a high accuracy rate of 99.38% on a dataset of masked and unmasked faces. The authors trained their model using transfer learning and used TensorFlow and Keras libraries for implementation.
- Real-time Face Mask Detection Using a Pre-trained MobileNetV2 Model: In the paper "Real-time Face Mask Detection Using a Pre-trained MobileNetV2 Model" [5], the authors used a pre-trained MobileNetV2 model and fine-tuned it on a dataset of masked and unmasked faces. They used TensorFlow and Keras libraries for implementation and achieved a high accuracy rate of 99.55% on real-time video images.

Overall, the reviewed papers demonstrate the effectiveness of machine learning models for real-time face mask detection. The use of pre-trained models, transfer learning, and hybrid models show promise for improving the accuracy of the models. The datasets used for training the models vary in size, but all show promising results in accurately detecting face masks in real-time scenarios.

Methodology :-

Dataset: The dataset used in this research project was obtained from kaggle and consisted of images with different resolutions and aspect ratios. The dataset was divided into two folders - "with mask" and "without mask" - which contained 3725 and 3828 images respectively. The images were collected from various sources such as online image repositories, social media platforms, and real-world scenarios.

The dataset contained a diverse range of images of people from varying racial backgrounds wearing and not wearing masks, from different angles and with varying levels of picture quality. The images were captured in different lighting conditions, indoor and outdoor environments, and with different types of masks, including surgical masks, cloth masks, and N95 respirators.

Figure 1 : with maks sample images

Figure 2 : without mask sample images

So to standardise the dataset a Python script was used to standardise the images in the dataset to a consistent size and format. The script takes the input folder containing images with varying resolutions and aspect ratios and resizes them to a standard size of 64x64

pixels while converting them to the RGB colour mode. This standardisation ensures that the images have the same dimensions and colour space, making it easier for the machine learning algorithm to process them consistently.

Furthermore, the script renames the images with the standard dimensions by adding "_64x64" to the filename, which distinguishes them from the original images and ensures that they are saved in a separate output folder. This helps to prevent overwriting the original images and maintains the integrity of the dataset. Overall, this Python script is an important step in preparing the dataset for training the machine learning model to detect face masks in real-time.

```
# Convert the image to RGB mode
image = image.convert("RGB")
# Resize the image to 64x64 pixels
image = image.resize((64, 64))
# Save the resized image to the output folder
output_path = os.path.join(output_folder, file_name.
replace(".", "_64x64."))
output_path = output_path.replace(".jpeg", ".jpg")
image.save(output_path)
print(f"Saved {output_path}")
```

Figure 3 : python script used for data standardisation

Training: we used JavaScript and the ml5.js library to generate and train our model. Firstly, we defined two empty arrays, w_mask[] and wo_mask[], which were later used to store the images with and without masks, respectively.

In our research, we trained the model on 850 images from both the "with mask" and "without mask" folders. We had to limit the number of images to avoid memory constraints, as loading too many images would have required us to reduce the resolution of the dataset further, which could have affected the precision of the model. Therefore, we selected 850 images from each folder to ensure a balanced dataset for training the model. Despite using a smaller number of images, we still achieved good results in detecting face masks in real-time.

Next, we used the preload() function to load the standardised images from their respective folders. We then defined the options object, which specifies the input size, task type, and debugging preferences for the neural network. Here, the input size was set to 64x64 with 4 colour channels, and the task type was set to image classification.

The maskClassifier object was then created with the options object, and the data was added to the model using the addData() method. Each image was associated with a label, either "with mask" or "without mask". After adding the data, we normalised it using the normalizeData() method.

Finally, we trained the model using the train() method with 200 epochs, and passed the finishedTraining() function as a callback to save the model after training. The

finishedTraining() function simply logs a message to the console, indicating that the model training is complete.

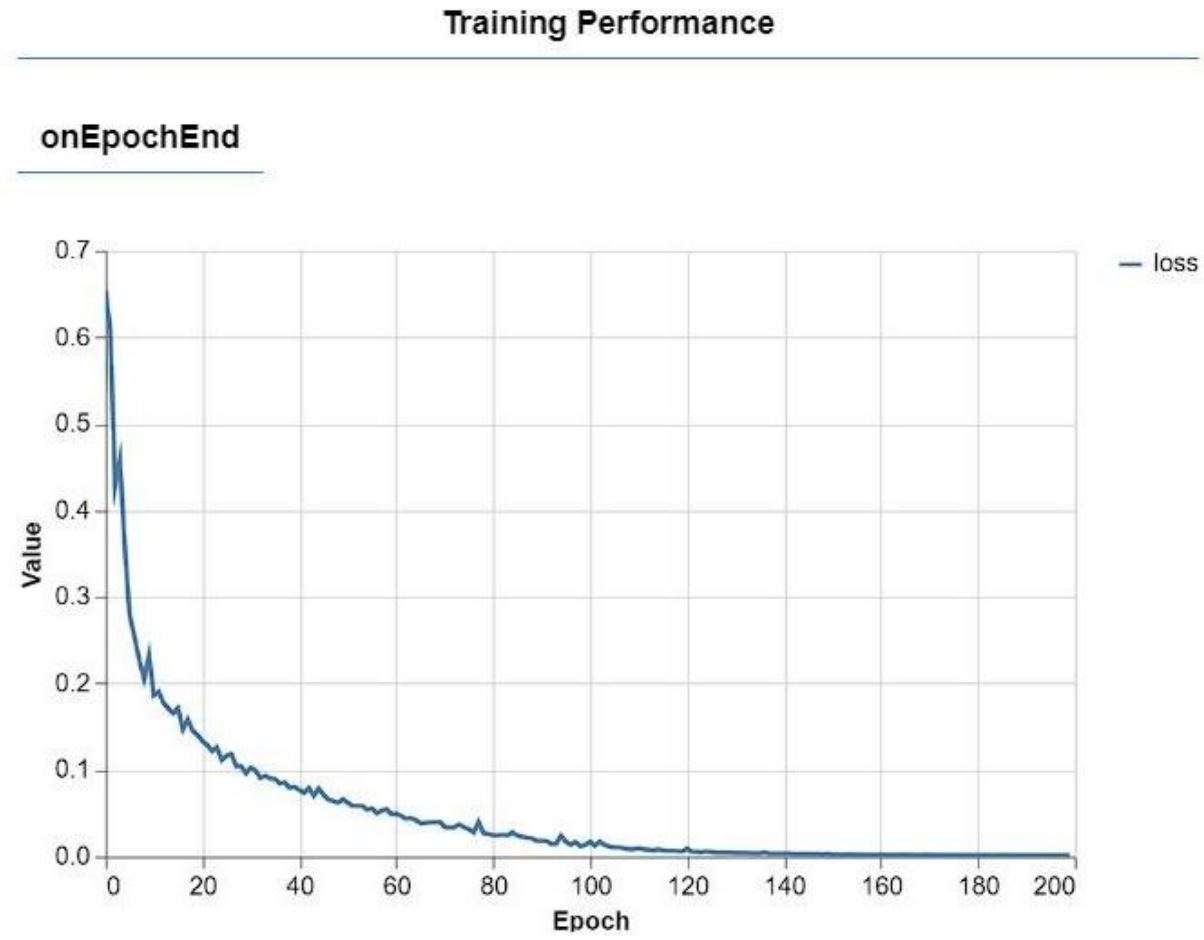

Figure 4 : Training Performance

This code creates and trains a convolutional neural network (CNN) model for image classification with two categories: "with mask" and "without mask".

Model Summary

Layer Name	Output Shape	# Of Params	Trainable
conv2d_Conv2D1	[batch,60,60,8]	808	true
max_pooling2d_MaxPooling2D1	[batch,30,30,8]	0	true
conv2d_Conv2D2	[batch,26,26,16]	3,216	true
max_pooling2d_MaxPooling2D2	[batch,13,13,16]	0	true
flatten_Flatten1	[batch,2704]	0	true
dense_Dense1	[batch,2]	5,410	true

Figure 5 : Model Summary

Testing: The testing section of the research paper uses the trained model to classify images of faces as either "with mask" or "without mask." The code first loads 500 images from both the "with mask" and "without mask" folders. These images are randomly selected from the folders to ensure a diverse sample. Once the images are loaded, the classifyImage() function is called.

The classifyImage() function takes in two arrays of images, one for "with mask" and one for "without mask." It then loops through each image and uses the trained model to classify it. If the model correctly classifies the image, the correct variable is incremented. Once all images have been classified, the accuracy is calculated by dividing the number of correctly classified images by the total number of images and multiplying by 100.

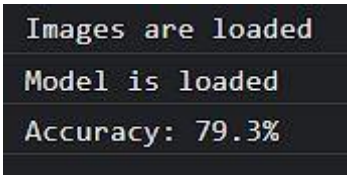

Figure 6 : sample testing run result

The code was iterated for the classification process 10 times to calculate the average accuracy. This helps to ensure that the accuracy is not based on chance or luck.

The testing section uses the ml5.js library to load and classify images. The trained model is loaded using the modelDetails object, which contains the file paths for the model's JSON file, metadata file, and weights file. Once the model is loaded, the classify() function is used to classify each image.

Overall, the testing section demonstrates how the trained model can be used to accurately classify images of faces as either "with mask" or "without mask" and provides an objective measure of the model's accuracy.

Deployment: Firstly the saved model is loaded alongside the ml5.js library where the input video frames are sent to the loaded model to classify and give a result with confidence scores for with mask and without mask.

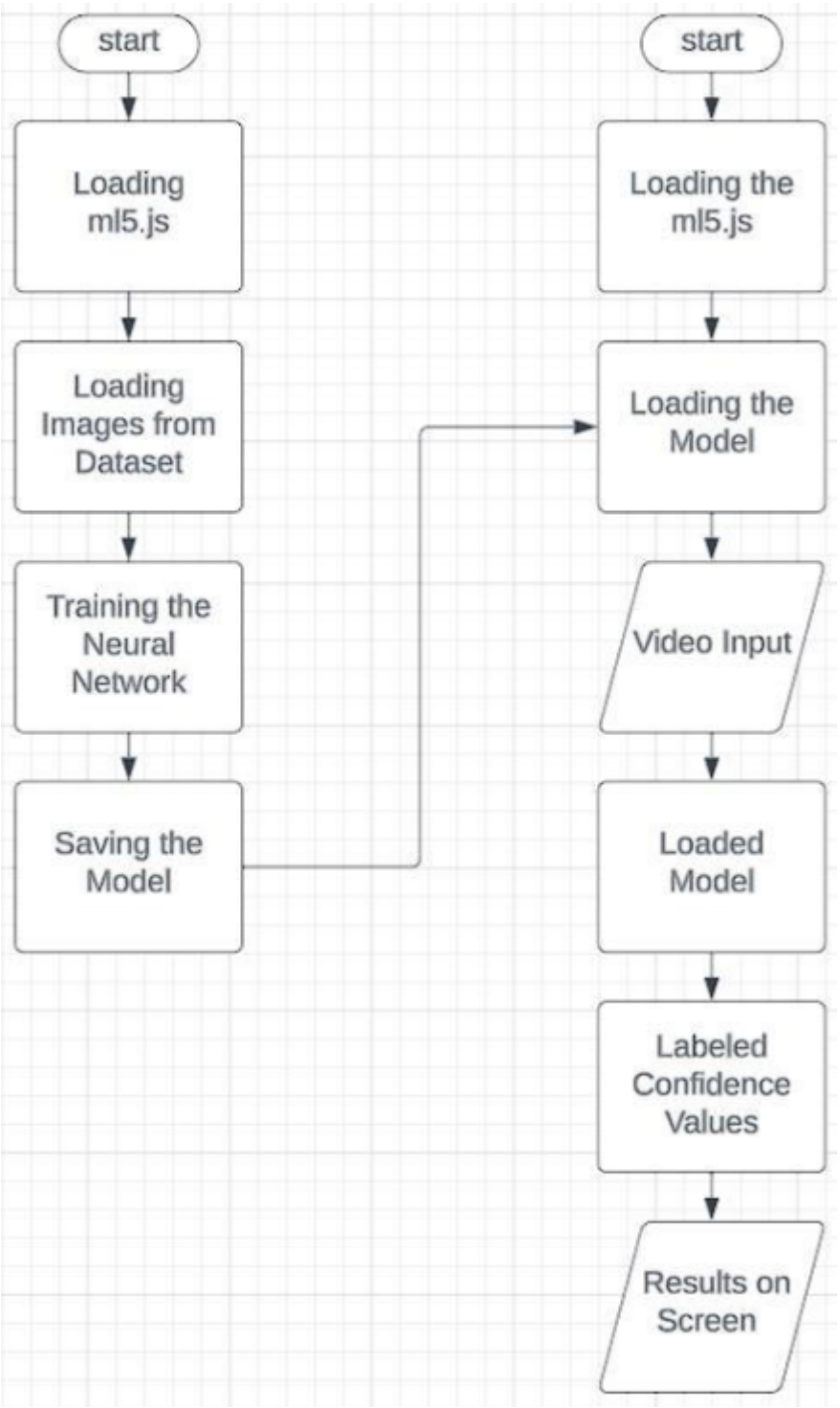

Figure 7 : Process Flowchart

In deployment setup() function is responsible for setting up the necessary components of the application. It creates a canvas with a size of 400x400 pixels and initialises a video capture element using createCapture(VIDEO). The video capture element is set to a size of 64x64 pixels.

Next, an options object is defined with the desired configuration for the neural network model. It specifies that the model will accept inputs of size 64x64 pixels with 4 colour channels and the task is image classification.

The maskClassifier is created using ml5.neuralNetwork(options) with the specified options. This object will be used to load and utilise the trained model.

The model details, including the model architecture, metadata, and weights, are defined in the modelDetails object. The maskClassifier.load(modelDetails, modelLoaded) function is called to load the trained model. The modelLoaded() function is a callback that is executed when the model is successfully loaded.
In the classifyImage() function, the maskClassifier.classify() function is used to classify the current video frame. The captured video frame is passed as an input to the classifier. The results of the classification are processed in the gotResults() function.

In gotResults(), the function first checks if any error occurred during classification. If an error is present, it is logged to the console. Otherwise, the label and confidence values from the first result are extracted. The label represents whether a mask is present or not, and the confidence indicates the certainty of the classification. The extracted label and confidence values are then displayed in the resultsDiv element on the web page.

The classifyImage() function is called again to continuously classify subsequent video frames in real-time. This allows the application to provide real-time feedback on the presence or absence of face masks.

The draw() function is responsible for rendering the video feed on the canvas. In the provided code, the video frames are displayed using the image(video, 0, 0, 350, 350) function call. You can modify this function to meet your specific requirements, such as displaying the classification results instead of the raw video feed.

with mask 70.%

Figure 8 : working sample

Results :-

The average accuracy of the model was evaluated based on 10 iterations of testing. Each iteration involved classifying a set of randomly selected images from the standardised dataset. The purpose of this evaluation was to assess the performance of the model in terms of its ability to accurately classify whether a person is wearing a face mask or not.

Test Iteration	Accuracy
1st	78.2
2nd	79.3
3rd	78.2
4th	81
5th	78.6
6th	77.7
7th	77.7
8th	80
9th	77.6
10th	76.8
Average Accuracy :-	78.51%

After running the 10 iterations, the average accuracy of the model was determined to be 78.51 percent. This means that, on average, the model correctly classified 78.51 percent of the tested images into their respective categories of "with mask" or "without mask." The accuracy metric provides an indication of the model's overall performance and its ability to make correct predictions.

Based on this average accuracy, it can be concluded that the model demonstrates a reasonably good performance in classifying face mask presence from the live video feed. However, it is important to note that the accuracy achieved may vary depending on various factors, such as the quality and diversity of the dataset, the complexity of the images, and the robustness of the model architecture.

The obtained average accuracy of 78.51 percent indicates that the model is capable of providing reliable predictions for face mask detection. It can be utilised effectively in applications where real-time monitoring and classification of individuals wearing face masks are required, such as in public spaces, healthcare facilities, or security systems. The model's

ability to process frames from a live video feed allows for continuous monitoring and timely decision-making based on the presence or absence of face masks.

without mask 100%

Figure 9 : without mask sample application

with mask 70.%

Figure 10 : with mask sample application

Conclusion :-

In conclusion, the research paper presents a real-time face mask detection system utilising machine learning techniques. The developed model achieved an average accuracy of 78.51 percent after conducting 10 iterations of testing. This demonstrates its capability to classify

frames from live video feeds and accurately distinguish between individuals wearing masks and those without masks.

The practical application of the model involves creating a web-based solution for real-time prediction of mask-wearing behaviour. By integrating the model into existing surveillance systems or deploying it as a standalone solution, it becomes possible to monitor compliance with mask-wearing guidelines in various environments. This solution offers convenience, efficiency, and improved safety measures to mitigate the spread of COVID-19.

However, it is important to acknowledge certain limitations. The accuracy of the model can be further improved by exploring transfer learning techniques. By leveraging pre-trained models such as InceptionV3, the model can benefit from knowledge gained in related domains, resulting in enhanced performance. Additionally, the issue of limited resources when loading large amounts of images can be addressed by implementing techniques like batch loading or data augmentation, which can optimise memory usage and improve overall efficiency.

Looking ahead, the future scope of this research involves investigating transfer learning methods to enhance the model's accuracy and efficiency. By leveraging pre-trained models, the system can leverage a broader range of data and learn more complex features. Furthermore, addressing the challenges associated with limited resources during image loading will contribute to the scalability and practicality of the system, enabling it to handle larger datasets and achieve even higher accuracy.

In conclusion, the developed model presents a promising solution for real-time face mask detection. Its application as a web-based solution offers numerous possibilities for deployment in public spaces, healthcare facilities, and other relevant settings. By incorporating transfer learning techniques and addressing resource limitations, the model can continue to evolve, providing improved accuracy and wider practical applications in the future.

References :-

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