A

MINI PROJECT REPORT

on

FACE MASK DETECTION USING MACHINE LEARNING

Submitted to

JAWAHARLAL NEHRU TECHNOLOGICAL UNIVERSITY, HYDERABAD

In partial fulfilment of the requirement for the award of the degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

(DATA SCIENCE)

By

(BATCH: A-20)

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Under the Guidance of

Mrs. G. Annapurna

Assistant Professor

EMPOWERING THROUGH INNOVATIONS

MLRS

MARRI LAXMAN REDDY

INSTITUTE OF TECHNOLOGY & MANAGEMENT

(AN AUTONOMOUS INSTITUTION)

(Approved by AICTE, New Delhi & Affiliated to JNTUH, Hyderabad)

NAAC Accredited Institution with 'A' Grade & Recognized Under Section2(f) & 12(B)of the UGC act,1956

JUNE, 2025

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COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

CERTIFICATE

Date:

This is to certify that the project work entitled "**FACE MASK DETECTION USING MACHINE LEARNING**"work done by N.JYOYHI NANDHA KISHORE REDDY(227Y1A6781), KARAN PASWAN(227Y1A6782) and POLU KAVYA (227Y1A6784)

students of Department of Computer Science Data Science Engineering, is a record of bonafide work carried out by the members during a period from January, 2025 to June, 2025 under the supervision of **Dr.A.Arun Kumar, Professor and Head Of The Department, Department (Data Science)**. This project is done as a fulfilment of obtaining Bachelor of Technology Degree to be awarded by Jawaharlal Nehru Technological University Hyderabad, Hyderabad.

The matter embodied in this project report has not been submitted by us to any other university for the award of any other degree.

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Date: **(Mrs.G.Annapurna)**

N. JYOTHI NANDHA KARAN PASWAN POLU KAVYA KISHORE REDDY

The Viva-Voce Examination of above students, has been held on……………………

External Examiner **Principal/Director** **Head of the Department**

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
NLP	Natural Language Processing
CSV	Comma-Separated Values
CNN	Convolutional Neural Network
API	Application Programming Interface
OpenCV	Open Source Computer Vision Library
GUI	Graphical User Interface
UI	User Interface
ANN	Artificial Neural Network

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Abstract Performa

MINI PROJECT

Year & Branch: III, CSD	Section: A	Batch No.: B20
Academic Year: 2024 – 2025		Regulation: R22
Student Registration Details	Name	Roll Number
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Name of the Guide & Designation	Mrs.G.Annapurna, Assistant Professor	
Area (Domain) of the Project	Machine learning	
Title of the Project	FACE MASK DETECTION USING MACHINE LEARNING	
Tools Required	Flask, IDLE, Open CV, TensorFlow, Keras	

Abstract

Background/Introduction

This project is a **Face Mask Detection using Machine Learning** that enables users to input relevant medical parameters and receive immediate predictions regarding their risk of heart disease.

Objectives.

To implement and compare Convolutional Neural Network (CNN) algorithm for accurate classification.

- Expected Results / Outcomes
- Prediction result
- Graphical visualization
- Comparative analysis
- Report exporting

Significance / Impact

This project promotes **accessible and proactive healthcare** by enabling users to assess disease risk without needing invasive tests or hospital visits.

PROJECT GUIDE **PROJECT COORDINATOR**

HEAD OF DEPARTMENT

ABSTRACT

In response to the global health c risis caused by COVID-19, face mask detection has emerged as a critical component in safeguarding public health and ensuring adherence to safety protocols. This project presents a robust and efficient Face Mask Detection system leveraging deep learning and computer vision techniques to automatically identify individuals wearing or not wearing face masks in real-time. Utilizing a Convolutional Neural Network (CNN) architecture, the model is trained on a diverse dataset encompassing various facial orientations, lighting conditions, and mask types to ensure high accuracy and generalizability. The system integrates seamlessly with existing surveillance infrastructure, enabling automated monitoring in high-traffic environments such as airports, schools, hospitals, and public transportation systems. This documentation outlines the system's architecture, dataset preprocessing, model training and evaluation, as well as deployment strategies. The proposed solution not only enhances public safety but also demonstrates the transformative potential of AI in solving real-world challenges.

CHAPTER 1

INTRODUCTION

Face detection is a fundamental computer vision task that involves identifying and locating human faces in digital images or video streams. It serves as the first step in a wide range of applications, including facial recognition, emotion detection, surveillance, augmented reality, and human-computer interaction.

With the rapid advancement of artificial intelligence (AI), machine learning (ML) techniques have significantly improved the accuracy and efficiency of face detection systems. Traditional methods relied heavily on handcrafted features and simple classifiers, while modern approaches leverage deep learning, particularly convolutional neural networks (CNNs), to automatically learn complex patterns in facial data.

Machine learning-based face detection works by training algorithms on large datasets of labeled images containing faces. The model learns to distinguish facial features such as eyes, nose, and mouth from non-facial elements by optimizing parameters that minimize classification errors. Once trained, the model can generalize to detect faces in new, unseen images with high precision.

The year 2020 has shown mankind some mindboggling series of events amongst which the COVID19 pandemic is the most life- changing event which has startled the world since the year began.

Affecting the health and lives of masses, COVID19 has called for strict measures to be followed in order to prevent the spread of disease. From the very basic hygiene standards to the treatments in the hospitals, people are doing all they can for their own and the society's safety; face masks are one of the personal protective equipment. People wear face masks once they step out of their homes and authorities strictly ensure that people are wearing face masks while they are in groups and public places. To monitor that people are following this basic safety principle, a strategy should be developed.

A face mask detector system can be implemented to check this. Face mask detection means to identify whether a person is wearing a mask or not. The first step to recognize the presence of a mask on the face is to detect the face, which makes the strategy divided into two parts: to detect faces and to detect masks on those faces.

Face detection is one of the applications of object detection and can be used in many areas like security, biometrics, law enforcement and more. There are many detector systems developed around the world and being implemented. However, all this science needs optimization; a better, more precise detector, because the world cannot afford any more increase in corona cases.

1.1 MOTIVATION

Outbreak of the COVID-19 pandemic brought unprecedented challenges to global health systems, economies, and societies. Among the most effective and widely recommended preventive measures is the use of face masks in public spaces to reduce the transmission of the virus. However, ensuring widespread compliance with mask-wearing guidelines, especially in crowded or unsupervised environments, has proven to be a signific the ant challenge.

Manual enforcement of mask mandates is not only labor-intensive but also inefficient and impractical in many real-world scenarios. This challenge sparked the need for an automated, scalable, and intelligent solution. With the rapid advancement of machine learning and computer vision technologies, it has become feasible to develop systems that can automatically detect whether individuals are wearing face masks correctly.

The motivation behind this project is to leverage machine learning to create a reliable face mask detection system that can be deployed in public and private spaces to assist in monitoring compliance, reduce the burden on human enforcers, and contribute to safer environments. Beyond the context of COVID-19, this project also highlights the broader potential of AI-driven health and safety monitoring systems, paving the way for future innovations in public health surveillance.

1.2 PROBLEM STATEMENT

This project aims to address this gap by developing a machine learning-based face mask detection system capable of automatically identifying whether a person is wearing a face mask properly. The system must be robust against variations in lighting, facial orientation, occlusion, and the presence of multiple individuals in a frame. It should be capable of real-time performance and scalable deployment across a range of public and private settings, such as airports, schools, hospitals, public transport, and retail centers.the problem is to design and implement an automated, accurate, and efficient face mask detection system using machine learning techniques to support public health monitoring and policy enforcement in a practical, non-intrusive, and scalable manner.

1.2.1 Lack of Integrated Prediction and Strategy Tools

Most face mask detection systems using machine learning focus only on identifying whether a person is wearing a mask or not. They use image classification techniques, typically with Convolutional Neural Networks (CNNs), to perform this task. However, these systems usually work in isolation.

and do not include tools for predicting future behavior or planning responses.an effective system should not just detect mask usage but also analyze trends, predict non-compliance in certain areas, and help in decision-making. This would require combining detection with data analysis and strategy tools. The lack of this integration limits the system's usefulness in real-world scenarios, especially in managing public health and safety.

1.2.2 Limited Support for Multi-Format Input (CSV/Video)

Most face mask detection systems are designed to process real-time video streams or static images for prediction. However, they often lack flexibility in handling different input formats such as CSV files containing image paths, annotations, or pre-extracted features, and recorded video files for batch processing.

1.3 Objectives

The primary objective of this project is to design and implement an intelligent, automated system that utilizes machine learning—particularly deep learning techniques—to accurately detect and classify whether individuals are wearing face masks properly, improperly, or not at all. The system is intended to operate effectively on both static images and live video streams, making it adaptable for real-time surveillance applications in public and private settings.

This objective is grounded in the need to support public health measures, especially in response to pandemics like COVID-19, where mask-wearing plays a vital role in reducing the transmission of airborne diseases. Manual monitoring of mask compliance is labor-intensive, inconsistent, and infeasible in many real-world scenarios, particularly in high-density areas such as airports, hospitals, shopping centers, and public transport systems.

Therefore, automating this process using machine learning addresses both the scalability and reliability challenges of manual enforcement.Ultimately, the goal is to create a scalable, realtime, and accurate face mask detection system that not only enhances public safety during health crises but also lays the groundwork for future applications in intelligent surveillance, workplace safety, and AI-driven compliance monitoring.

1.3.1 To Design a Dual-Input Prediction System

The dual-input system will utilize convolutional neural networks (CNNs) for image-based predictions.

and integrate preprocessing pipelines for both video frames and CSV-referenced image paths. This allows for greater control over input data, model evaluation, and deployment settings. It also promotes a modular and scalable design, capable of being adapted to different surveillance or research environments.

1.4 Scope of the Project

The scope of this project encompasses the design, development, training, and deployment of an intelligent face mask detection system using machine learning techniques, specifically deep learning models like Convolutional Neural Networks (CNNs). The system is intended to identify whether individuals in an image or video frame are wearing face masks properly, improperly, or not at all.

This project addresses a real-world public health and safety concern, particularly relevant in the context of pandemic situations such as COVID-19, where mask-wearing is critical in preventing the spread of airborne diseases. The scope is broad yet focused, covering the following key areas:

1. Data Collection and Preprocessing

- Utilize publicly available datasets and/or collect custom datasets containing facial images with and without masks.

- Apply preprocessing techniques such as resizing, normalization, augmentation, and face detection to ensure quality input for model training.

2. Model Development

- Build a machine learning model (primarily using CNNs) capable of learning from labeled image data.

- Train and fine-tune the model to accurately classify images into categories such as "Mask," "No Mask," and optionally, "Improper Mask."

3. Dual Input Support

- Design the system to accept both live video streams (for real-time monitoring) and structured input files (e.g., CSV files containing image paths and labels) to increase flexibility.

4. Real-Time Detection and Monitoring

- Implement the model to work with webcam or CCTV feeds for real-time mask detection in public or private spaces such as schools, hospitals, offices, or transportation hubs.

5. Model Evaluation

- Test the model using performance metrics like accuracy, precision, recall, and F1-score to ensure robustness across diverse scenarios and demographics.

6. Application and Integration

- Enable easy deployment of the model in various environments through a simple user interface or integration with surveillance systems.

- Consider scalability, so the model can be adapted for large-scale use in smart cities or enterprises.

CHAPTER 2

LITERATURE SURVEY

Introduction

MobilenetV2: MobileNetV2 is a state of the art for mobile visual recognition including classification, object detection and semantic segmentation. This classifieruses Depth wise Separable Convolution which isintroduced to dramatically reduce the complexity costand model size of the network, and hence is suitable toMobile devices, or devices that have low computationalpower. Inverted residual structure is another excellent module included in MobileNetV2. Non-linearity in narrow layers is deleted. Best performance for object detection and semantic segmentation is achieved using MobileNetV2 as the backbone for feature extraction.

ResNet50: ResNet50 enables us to train deep neural networks with more than 150 layers. Prior to ResNet, training very deep neural networks was challenging due to the problem of vanishing gradients. The skip connection concept was first developed by ResNet.

ADAGRAD:Adagrad is an optimizer with parameter-specific learning rates, which are adapted relative to how frequently a parameter gets updated during training. The smaller the updates become when a parameter receives more updates.

ADAM: Adam is a first-order gradient-based stochastic objective function optimization algorithm based on adaptive estimations of lower-order moments. This method is computationally efficient and requires little memory to operate. It is an invariant to diagonal rescaling of the gradients, which is well suited for problems which are large in terms of dataand/or parameters. The hyper-parameters have straightforward interpretations and require little adjustment in most cases.

2.1 Analytics and AI Integration

Face mask detection is an essential computer vision task, especially in public health and surveillance. Integrating AI (Artificial Intelligence) and Analytics using Machine Learning (ML) provides not just detection capabilities, but actionable insights, predictive forecasting, and compliance monitoring in real-world environments.Integrating AI with analytics in face mask detection systems elevates them from simple detectors to intelligent, decision-support platforms. The synergy:

- Improves public safety.
- Helps organizations respond quickly.
- Enables data-driven policymaking.

2.2 Machine Learning in Face Mask Detection

Face mask detection is an application of computer vision and machine learning focused on identifying whether a person is wearing a face mask. This task became vital during the COVID19 pandemic to ensure public safety and compliance with health guidelines. The objective is to automatically detect and classify faces in images or video frames as either masked or unmasked, or sometimes even categorize improper mask usage.

2.2.1 Use of Logistic Regression

Face mask detection has become an essential computer vision problem in the context of public health monitoring and safety enforcement. The goal is to design systems that can automatically detect whether a person is wearing a mask or not, often using images or video feeds from surveillance cameras or mobile devices.Machine learning offers a variety of techniques for solving this classification problem. Logistic Regression (LR) is one of the earliest and simplest supervised learning algorithms used for binary classification tasks. Despite its simplicity, logistic regression remains relevant, especially when combined with robust feature extraction methods. It provides a baseline solution and is particularly useful in scenarios where interpretability and computational efficiency are important.

The first step involves detecting and extracting face regions from input images using face detection algorithms such as Haar cascades or Multi-task Cascaded Convolutional Networks (MTCNN). This isolates the face from the background to reduce noise and irrelevant information.The cropped face images are resized to a consistent dimension and normalized to maintain uniformity across samples.

2.2.2 Limitations of Black-box Models

It's challenging to explain why a model classifies a particular face as masked or unmasked. This hinders trust, especially in sensitive applications like public safety and health monitoring.It's challenging to explain why a model classifies a particular face as masked or unmasked. This hinders trust, especially in sensitive applications like public safety and health monitoring. If the training dataset lacks diversity (e.g., few examples of certain ethnicities, age groups, or mask styles), black-box models can develop biased predictions, reducing fairness and reliability.

2.3 Role of Natural Language Processing (NLP) in Face Mask Detection

Face mask detection is primarily a computer vision task, but real-world applications often involve multimodal systems that combine visual data with text or speech for richer understanding and interaction. NLP enables NLP can analyze textual or spoken inputs (e.g., user queries, instructions, or alerts) to provide context-aware responses. For example, a system detecting masks might also process user commands or explanations in natural language.After detecting mask compliance, the system may generate automated reports or alerts using natural language summaries — for example, "5 people without masks detected in the lobby." NLP helps transform raw detection results into understandable text.NLP techniques can assist in managing large datasets by processing textual annotations, descriptions, or tags associated with images used for mask detection model training.

2.4 Use of Web Technologies in ML Deployment

Deploying machine learning (ML) models for face mask detection involves making these models accessible, interactive, and efficient in real-world settings. Web technologies provide an ideal platform for deployment because they enable applications to run on diverse devices through browsers, removing the need for specialized software installations. By leveraging the ubiquity of the internet and advances in web frameworks, ML-powered face mask detection can be delivered to end-users globally with ease. These are used to build user interfaces (UIs) that interact with the user, such as HTML, CSS, and JavaScript, often supported by frameworks like React, Angular, or Vue.js. Server-side frameworks and languages like Node.js, Python(Flask,Django, FastAPI) that host the ML models and provide APIs for interaction.**:** HTTP/HTTPS, RESTful APIs, WebSockets enable data exchange between client and server.

2.5 Multi-Modal Data Analysis (CSV & Video)

Multi-modal data analysis involves integrating and processing different types of data sources to improve model performance, robustness, and contextual understanding. In the context of face mask detection, multi-modal data typically includes:Video Data:

Continuous visual streams from cameras showing people wearing or not wearing masks. Tabular Data (CSV): Structured data files containing related information such as timestamps, location metadata, temperature readings, or user demographic information. Combining these modalities allows machine learning models to leverage richer context and improve accuracy, decision-making, and monitoring capabilities.

Multi-modal learning deals with the challenge of processing and integrating information from multiple data modalities (e.g., vision, text, audio, tabular data). The key idea is that different modalities can provide complementary information, leading to a more comprehensive understanding and potentially better performance than using a single modality alone.

Information Redundancy and Complementarity: Different modalities might contain redundant information (e.g., the presence of a face might be evident in both video and metadata) or complementary information (e.g., video shows the mask, while location from CSV might indicate context-specific mask rules). Effective multi-modal learning leverages this complementarity.

Representation Learning: A significant aspect is learning joint or aligned representations of the data from different modalities. The goal is to map the modalities into a common space where their relationships can be effectively modeled.

Multi-modal data analysis combining video and CSV/tabular data significantly enhances machine learning-based face mask detection systems. It provides a more holistic understanding of mask compliance behavior, contextualizes detection events, and supports informed decisionmaking for health and safety management. Despite challenges like data synchronization and privacy, the fusion of heterogeneous data modalities is a promising direction for building robust, accurate, and scalable face mask detection solutions.

CHAPTER 3

SYSTEM ANALYSIS AND DESIGN Introduction

System Analysis and Design (SAD) is a methodical process for developing efficient, robust, and scalable systems. In the context of face mask detection using machine learning (ML), SAD helps to define the system's functionality, requirements, architecture, data flow, and integration mechanisms. This process ensures that the system aligns with both technical goals and realworld usability in environments such as public surveillance, hospitals, transportation hubs, or workplaces.

3.1 Existing System

The year 2020 has shown mankind some mind-boggling series of events amongst which the COVID-19 pandemic is the most lifechanging event which has startled the world since the year began. Affecting the health and lives of masses, COVID-19 has called for strict measures to be followed in order to prevent the spread of disease. From the very basic hygiene standards to the treatments in the hospitals, people are doing all they can for their own and the society’s safety; face masks are one of the personal protective equipment. People wear face masks once they step out of their homes and authorities strictly ensure that people are wearing face masks while they are in groups and public places

3.2 Limitations of Existing System

Despite the significant progress in face mask detection using machine learning (ML), existing systems still face several technical, operational, and ethical limitations. These limitations impact the accuracy, scalability, usability, and real-world deployment of such systems, especially in dynamic and uncontrolled environments.

a. Dataset Limitations

- Many existing systems are trained on limited or synthetic datasets that do not represent real-world diversity in facial features, mask types, lighting, and occlusion.

b. Overfitting to Training Data

- Machine learning models may perform well on training and validation datasets but fail to generalize to new environments, camera angles, or demographics due to overfitting.

c. Camera Quality and Angles

- Low-resolution or poorly positioned cameras can make face detection and mask classification unreliable.

- Angle variations (e.g., tilted head) affect the visibility of mask placement.

d. Real-Time Processing Limitations

- Some models, especially those with high accuracy (e.g., deep CNNs), are computationally intensive and not suitable for real-time inference on edge devices.

- High latency in real-time detection can delay alerts and actions, which is critical in high-traffic or security-sensitive areas.

e. Incomplete Detection Categories

- Many systems only classify two states: *mask* or *no mask*. This binary classification fails to identify:

3.3 Proposed System

The proposed system aims to enhance the performance, adaptability, and reliability of face mask detection using machine learning by addressing key shortcomings in existing models. It introduces a modular, real-time, and scalable architecture that combines computer vision, deep learning, and edge computing with privacy-aware design principles.Accurately detect whether individuals are:

Wearing a face mask correctly.Wearing a mask incorrectly (under the nose/chin).Not wearing a mask at all.Provide real-time analysis with minimal latency.Enable easy deployment on both edge and cloud environments.Preserve user privacy and comply with data protection norms.Offer analytics and reporting dashboards for public health monitoring

3.4 System Architecture

The Proposed approach comprises three phases. The first phase is preprocessing phase to prepare the dataset and detect the region of interest (ROI), i.e., face area. This research used the fine-tunes Residual Neural Network for constructing the model and trained the model to extract the Region of Interest (ROI) from each image present in the dataset. The second step divides the detected faces into three : unmasked faces, masked faces, and wrongly masked faces. The final phase detects the person's identity to allow authentication. At the sub-stage of this study, a Deep Learning model network will be trained and examined for detecting a face. This training database will be employed for the training network.

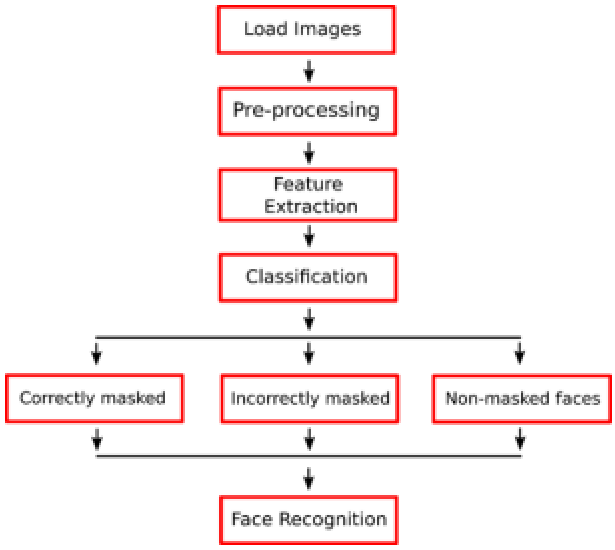

Figure 3.4 FACE MASK DETECTION– System Architecture Diagram

3.5 Module Description

There are two modules in this project.

•Training Data

•Detection Mask

Training Data: We choose Supervised Learning to train the data. Since most of the project outcome depends on how we train the data along with the consideration of accuracy, time, delay and other factors which improves the training model to be more efficient. In this first module the entire image dataset is trained. So the project is Data Centric. We first download the image dataset from Kaggle. There are categorised into 2 types:

a) Images with person with face mask

b) Images with person without face mask the dataset size is more than or equal to 1000 i.e 1000 of each category.

Next we need to train those images in training module with respective factors such as epoch, batch size, learning rate. It is based on the size of sample we need to define those factors

For our project

•Epoch =20

•Batch size=3

•Initial learning rate is 1e-4 (1/10000) or 0.0001

We found the image dataset from Kaggle and downloaded 1000 images for each category

•1000 image of with mask

•1000 images of without mask i.e. normal faces of human.

DETECTION MASK

•If it is mask: it will show confidence numeric value (eg:99.0% person wearing mask)

•If it is no mask: it will show confidence numeric value (eg:99.0% person not wearing mask)

By detecting a person whether he is wearing a mask or not. Based on the trained data the output will be given the trained data to be more distinct. The output is accurate every time irrespective of Race, Skin colour, Gender

•Racially Distinct: Asian, African, American, Caucasian, etc

•Skin Colour: Black, Brown, white, Whitish, etc

•Gender: Male, Female

3.6 Feasibility study

A feasibility study assesses the practicality, viability, and success potential of implementing a machine learning-based face mask detection system. This study covers multiple aspects: technical, economic, operational, legal, and schedule feasibility.

Technical Feasibility

Technical feasibility refers to the assessment of whether the current technological resources—both hardware and software—are sufficient to successfully design, develop, and deploy a system. In the context of face mask detection using machine learning, this analysis evaluates whether the necessary technical tools and infrastructure are available to implement the project effectively and efficiently.

Operational Feasibility

Operational feasibility refers to the degree to which a proposed system is capable of functioning effectively within the current operational environment. In other words, it assesses whether the system can be successfully used, maintained, and integrated into the day-to-day operations of an organization.

In the context of a **face mask detection system** powered by **machine learning**, operational feasibility is essential to determine whether the system will be accepted by users, fulfill the intended purpose, and improve operational efficiency without causing disruptions.

Economic Feasibility

Economic feasibility refers to the assessment of whether the proposed system is financially viable. It involves a cost-benefit analysis to determine if the expected benefits justify the investments made in terms of time, money, and resources.

For a **face mask detection system using machine learning**, economic feasibility is particularly important for stakeholders and decision-makers considering deployment at scale.

Type	**Evaluation**
Technical Feasibility	whether it is technically possible to develop and implement the proposed solution
Operational Feasibility	Designed for ease of use by non-technical users with intuitive UI.
Economic Feasibility	Uses free tools and runs on basic computing hardware, making it cost-effective.

table 3.6- feasibility study

3.7 Requirement Analysis

Requirement analysis is a critical phase in the software development lifecycle, focusing on identifying and documenting the functional and non-functional requirements that the system must fulfill. It ensures that the developed system aligns with user needs and operational constraints.

For a face mask detection system using machine learning, requirement analysis involves understanding the scope, technical needs, user expectations, and environmental conditions where the system will operate.

Functional requirements

Functional requirements describe the specific behaviors and functions the system must perform to fulfill its intended purpose. For a face mask detection system, these requirements focus on detecting faces, classifying mask usage, and interacting with users or other systems.

Requirement ID	**Description**
Face Detection	Detect multiple faces accurately in images/video
Mask Classification	Classify mask-wearing status: mask/no mask/incorrect wear
User Interface	Display live video, labels, alerts, and reports
System Integration	Provide API for integration with external systems

table 3.7.1 functional requirements

Non-Functional Requirements

Non-functional requirements specify the criteria that judge the operation of a system, rather than specific behaviors or functions. They describe system attributes such as performance, usability, reliability, and security, ensuring the system works effectively under various conditions.

Requirement ID	Description
Performance	Low latency, real-time processing, high accuracy
Reliability	continuous operation,error handling,consistent detection
Usability	intuitive UI, clear alerts, user-friendly
Maintainability	Modular design,easy updates,retraining support

table 3.7.2 Non-Functional requriements

CHAPTER 4 IMPLEMENTAT ION

1. Data Collection & Preprocessing:

- Collected a dataset of face images categorized as 'with_mask 'and 'without_mask'. - Images were resized, normalized, and converted into NumPy arrays. Labels were encoded as categorical values (0 for without mask, 1 for with mask).

2. Model Building:

- A Convolutional Neural Network (CNN) was used for training.

- Model consists of multiple convolutional and max-pooling layers followed by dense layers.

3. Model Evaluation:

- Accuracy, confusion matrix, and classification report were generated.

4. Real-Time Detection:

- A webcam feed was integrated using OpenCV.

- Face regions were detected using Haar Cascade classifier.

4.1 Tools and Technologies Used

- Programming Language: Python 3.x

- Libraries & Frameworks:

- TensorFlow / Keras

- OpenCV

- NumPy

- Matplotlib

- Scikit-learn

- Hardware: Laptop with webcam

- IDE: IDLE or cmd

4.2 Dataset Description

- Two folders: with_mask, without_mask

- Total images: ~1376

- Image Dimensions: 100x100 pixels

- Labels: Binary classification (0 - No Mask, 1 - With Mask)

4.3 Machine Learning Implementation

Model Architecture:

Input Layer: (100, 100, 3)

Conv2D -> ReLU -> MaxPooling2D

Conv2D -> ReLU -> MaxPooling2D

Flatten -> Dense -> Dropout

Output Layer: Softmax (2 units)

Training Configuration:

- Loss Function: Categorical Crossentropy

- Optimizer: Adam

- Epochs: 10-20

- Batch Size: 32 Model Saving:

- The trained model is saved as mask_detection_model.h5

4.4 Acceptance Testing

redelivery testing in which entire system is tested at clients site on real world data to find errors. This testing is also called as Formal testing with respect to user needs and requirements, and business processes conducted to determine whether or not a system satisfies the acceptance criteria and to enable the user and customers or authorized entity to determine also called as Formal testing with respect to user needs and requirements, and business processes conducted to determine whether or not a system It is a level of software testing where system is tested for acceptability. The purpose of this testing is to evaluate the systems compliance with the business requirements and assess whether it is acceptable for delivery. It is a redelivery testing in which entire system is tested at clients site on real world data to find errors

S.NO	TEST CASES	ACTUAL RESULTS	EXPECTED RESULTS	PASS/FAIL
1	Training the images of without mask	Dataset Category Successfully Trained	Dataset Category Trained Successfully	PASS
2	Training the images of with mask	Dataset Category Successfully Trained	Dataset Category Successfully Trained	PASS
3	Accessing the System Camera	Successfully Accessed	Successfully Accessed	PASS
4	Evaluate the output for person wearing mask	Output shown as Mask	Output shown as Mask	PASS
5	Evaluate the output for person not wearing mask	Output shown as No Mask	Output shown as No Mask	PASS
6	Show numerical data prediction for person wearing mask	Showed up to 100% If yes	Showed up to 100% If yes	PASS
7	Show numerical data prediction for person not wearing mask	Showed up to 100% If yes	Showed up to 100% If yes	PASS

table 4.4 test case table

Training Module


```
Microsoft Windows [Version 10.0.19041.1052]
(c) Microsoft Corporation. All rights reserved.

E:\Mask Detection\CODE\Face-Mask-Detection-master>python train_mask_detector.py
2021-07-01 16:59:45.772900: W tensorflow/stream_executor/platform/default/dso_loader.cc:60] Could not load dynamic library 'cudart64_110.dll'; dlerror: cudar
2021-07-01 16:59:45.773708: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU set up on your machine.
[INFO] loading images...
```

fig 4.4.1 Training module

Detection Module:

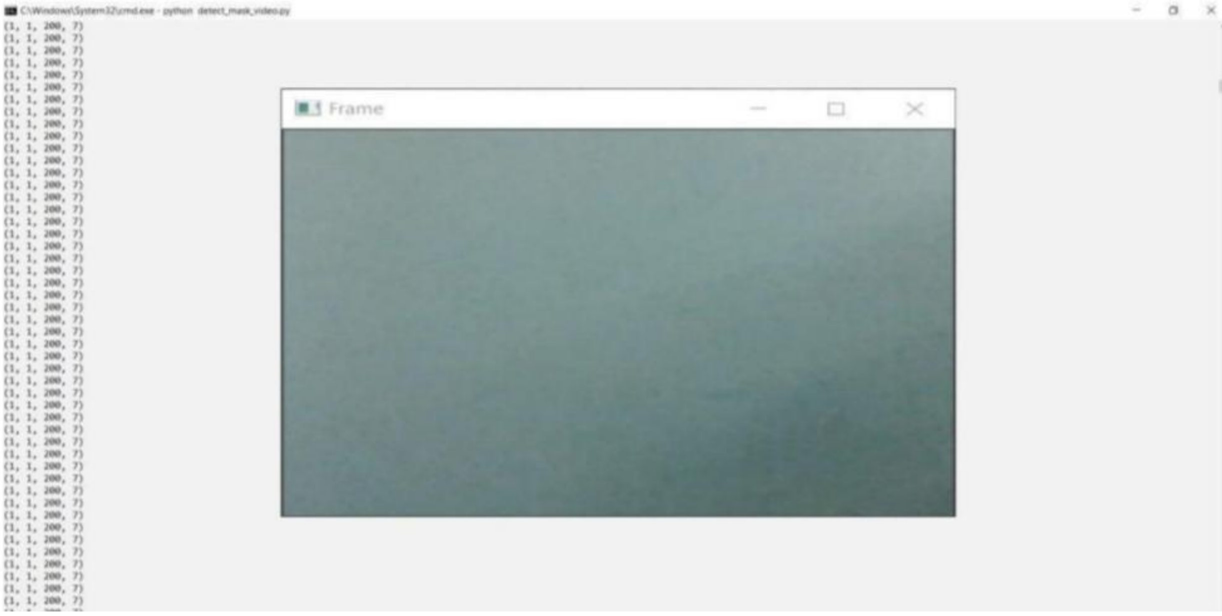

fig 4.4.2 detection module

Training Graph

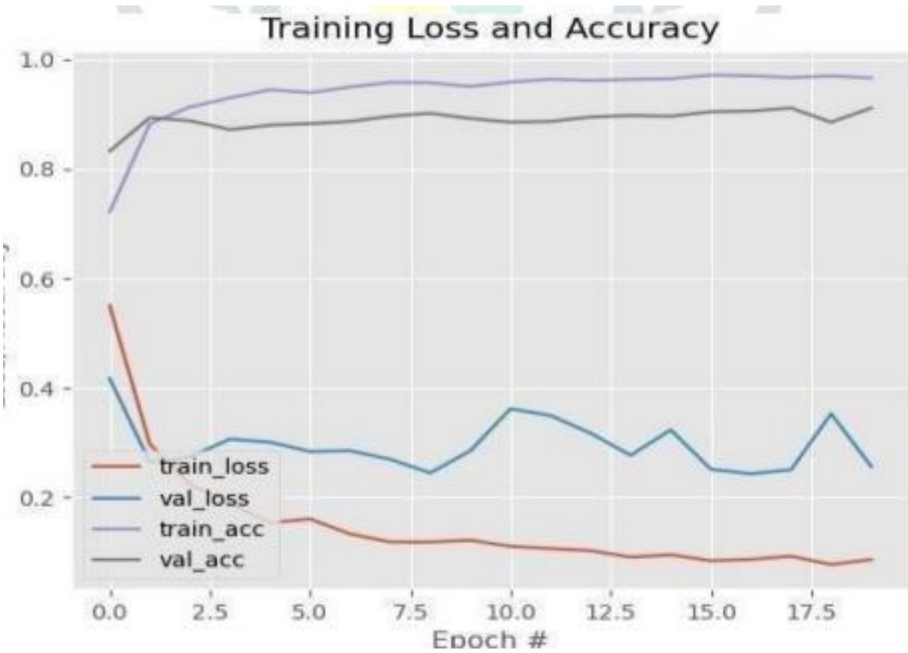

fig 4.4.3 training graph

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Strategy Suggestions

A successful face mask detection system involves a sequence of well-defined strategies that cover data collection, model development, deployment, and continuous improvement. These strategies ensure that the system is accurate, efficient, scalable, and reliable in real-world aaknesses, and areas for improvement in face mask detection systems.

5.2 Observations

Face mask detection using machine learning has gained wide attention due to its critical role in ensuring public health compliance, especially during pandemics. Through the process of developing, training, and testing such systems, various technical, behavioral, and environmental observations can be made. These observations help in identifying strengths, weaknesses, and areas for improvement in face mask detection systems.

High Accuracy with Clean Data: Pretrained deep learning models like MobileNetV2 or ResNet50 perform well when trained on high-quality, well-labeled datasets. **Accuracy Drop in Real-World Conditions**: The model may perform worse in practical settings with varied lighting, occlusion (e.g., sunglasses, hands), and poor camera angles.

Resolutionand Camera Quality: Low-resolution input or poor-quality video streams reduce face and mask recognition accuracy.

Multiple Faces in Frame: Performance can degrade when multiple people are present, especially if faces are at different distances or sizes.

CHAPTER 6
CONCLUSION AND FUTURE SCOPE

The development and deployment of a **Face Mask Detection System using Machine Learning** have proven to be a powerful tool in enforcing public health measures, particularly during pandemics like COVID-19. By leveraging computer vision and deep learning techniques, these systems can automatically detect whether individuals are wearing face masks properly in real-time video streams or images.Throughout this project, various models and technologies—such as Convolutional Neural Networks (CNNs), MobileNetV2, and YOLO—have been utilized for accurate and efficient mask detection. Data preprocessing, augmentation, and model optimization have played a crucial role in enhancing performance across different environments and camera conditions.

By embracing these enhancements, face mask detection systems can evolve from simple compliance tools to intelligent, ethical, and scalable health-monitoring platforms, ensuring greater safety and awareness in public and private spaces

6.1 Limitations

Data-Related Limitations

- Insufficient Diversity in Datasets: Many datasets used to train models lack diversity in terms of ethnicity, age, lighting, background, and camera angles, leading to biased or inaccuratedetection.
- Improper Mask Wearing Detection: It is significantly more difficult for models to identify partially covered faces or improperly worn masks (e.g., below the nose).

Model-Related Limitations

- Overfitting on Training Data: If not properly validated, the model may perform well on training data but fail to generalize to unseen data.

- Slow Inference on Edge Devices: High-accuracy models like ResNet or Inception are often too computationally heavy for real-time use on resource-constrained devices

6.2 Future Enhancements

Face mask detection systems built using machine learning have emerged as crucial tools during global health emergencies, notably the COVID-19 pandemic. These systems use computer vision and deep learning techniques to detect whether individuals are wearing masks in public or enclosed spaces. While current models provide reasonable accuracy and performance, there exists vast potential for future enhancements. These enhancements aim to improve system reliability, scalability, efficiency, and ethical deployment in diverse, real-world scenarios

1. Improved Model Generalization

- **Use of Transformer Architectures**: Incorporate Vision Transformers (ViT) or hybrid CNN-transformer models for better contextual understanding, especially in varied lighting and occlusion scenarios.
- **Domain Adaptation**: Develop models that adapt across domains (e.g., different cultures, facial structures, camera types) without retraining.
- **Self-Supervised Learning**: Train models with limited labeled data using contrastive or masked image modeling techniques

2. Multi-Label and Multi-Class Detection

- **Mask Type Classification**: Classify different mask types (surgical, cloth, N95) and improper usage (nose exposed, under chin).
- **Emotion + Mask Detection**: Simultaneously detect emotion while wearing a mask for mental health or customer service applications.

3. Robustness to Real-World Challenges

- **Adversarial Robustness**: Improve resistance to adversarial examples (e.g., mask designs that confuse detection systems).
- **Occlusion Handling**: Enhance detection under partial occlusions, such as hands or glasses interfering with face visibility.
- **Low-Resolution Video Streams**: Optimize models for low-quality surveillance footage

4. Real-Time and Edge Deployment

- **Lightweight Architectures**: Develop optimized models (e.g., MobileNetV3, EfficientNet-Lite) for deployment on edge devices like security cameras or Raspberry Pi.
- **Quantization and Pruning**: Use model compression techniques to reduce latency and power consumption without sacrificing much accuracy

OUTPUT

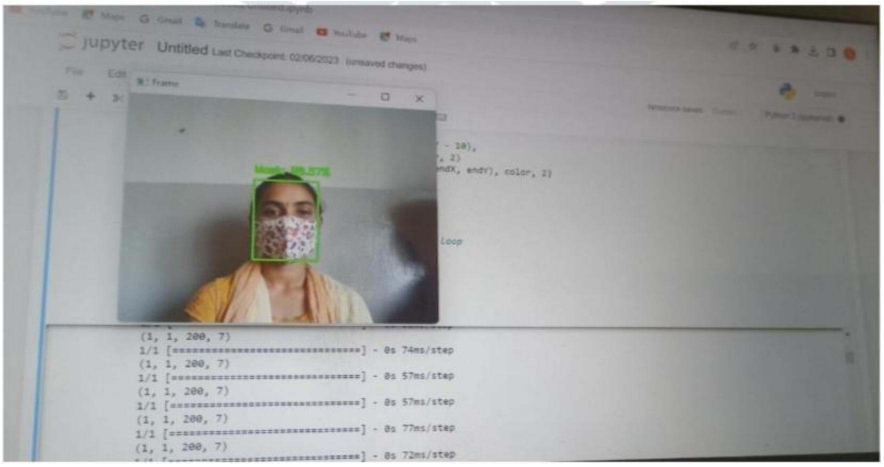

fig 6.3.1 with mask

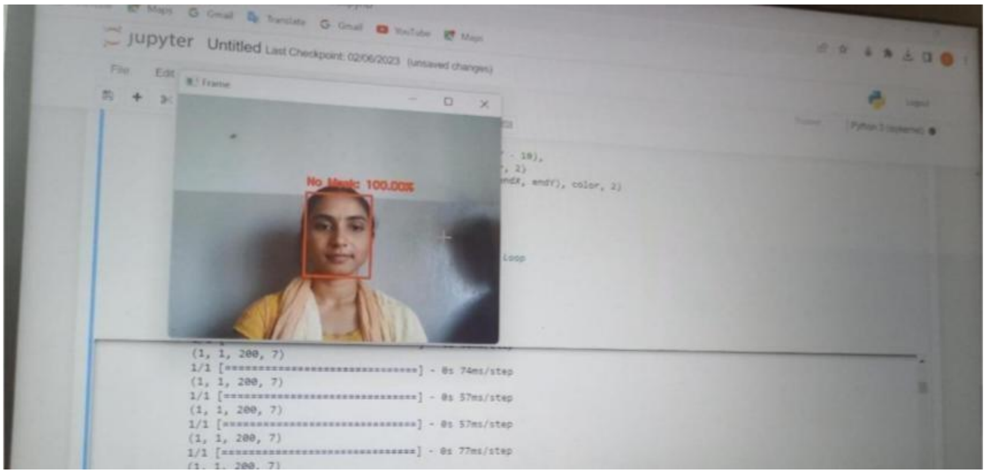

fig 6.3.2 without mask

Conclusion

The experimental analysis shows that the proposed method can be successfully exploited for face mask violation detection. It is a real time software application which can be deployed in smart cc tv surveillance, public areas like airports,malls,.etc where mask is necessary. Only the software it can be extensible to work along with other IOT devices to deny permit or closing doors at corporate office Moreover, we highlight that it is working also on device with limited computational capability and it is able to process in real time images and video streams, making our proposal applicable in the real world. Taking in to account above mentioned details, we can make the conclusion that the Mask detection project works in real time and be very useful in present situation. This application is build using python, python IDLE

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