CourseProjectTopicTitle: Face Mask Detection

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Chapter1:Introduction

Since the COVID-19 pandemic, wearing masks has become a key safety rule (Batra & Singh, 2021). However, it is hard for humans to check everyone manually. This project describes an automatic **Face Mask Detection System** that uses computer vision (Bradski, 2000) and deep learning (Abadi et al., 2016) to find faces and check for masks in real-time. The goal is to make public places like schools and malls safer (Gupta & Gupta, 2020). We followed the **Waterfall Model** for software development, which means we finished one step (like design) before moving to the next (like coding).

1.1 Background of Related Projects

After the COVID-19 pandemic, many people started to use face masks to stop the spread of the virus. Checking if everyone wears a mask in public places is hard for humans to do.
Some researchers and students have made computer systems that can detect faces and check if a person wears a mask. For example, projects using **CNN (Convolutional Neural Networks)** and **OpenCV** showed good results.
This project follows the same idea to build a system that can detect masks using Python and machine learning.

1.2 Project Description

This project is about creating a **Face Mask Detection System** that can see if a person wears a mask or not by using a camera or images.
It will use computer vision and deep learning to:

- Find a person's face, and
- Classify it as **"With Mask"** or **"Without Mask."**

The program will work in real time and show the result on the screen using a webcam.

1.3 Benefit of Research Related to the Industry

This research can help many industries and workplaces.

- It helps **keep people safe** by checking if everyone wears a mask.
- It **saves time and effort** because it works automatically.
- It can be used in **offices, schools, hospitals, and malls**.
- It shows how **artificial intelligence (AI)** can solve real-world problems.

1.4 Project Problem Statement

During the pandemic, many people did not follow mask rules. Checking mask use by humans takes a lot of time and can make mistakes.

There is a need for an **automatic system** that can **detect people with and without masks** in real time to make the process faster and more accurate.

1.5 Project Goals and Objectives

Goal:
To create a computer program that can detect if a person is wearing a face mask or not.

Objectives:

- To collect and prepare images of people with and without masks.
- To train a model to recognize masks using deep learning.
- To test the model with live camera or video.
- To show the results clearly on the screen.
- To check how accurate the system is.

1.6 Project Scope and Limitations

Scope:

- The system will only check for face masks.
- It will work with pictures and live video.
- It is for school and learning purposes.
- In the future, it can be improved to detect incorrect mask use.

Limitations:

- It may not work well in dark light or when the face is covered.
- Accuracy depends on the quality of the dataset.
- It needs a good computer to run smoothly.

1.7 Project Proposed Solution

The proposed solution is a **Face Mask Detection System** that uses **AI and image detection**.
The system will:

1. Detect faces using OpenCV.
2. Use a trained model to check if the person has a mask or not.
3. Show a box and label around the face — for example, “Mask” or “No Mask.”
4. Give accurate and quick results.

This system can help monitor mask use automatically and safely.

1.8 Project Software Development Model

This project will use the **Waterfall Model**, which means steps go one after another:

1. **Requirement Analysis:** Understand what the project needs.
2. **Design:** Plan how the system will work.
3. **Implementation:** Write and train the code and model.
4. **Testing:** Check if it works correctly.
5. **Deployment:** Run the final system.
6. **Maintenance:** Improve it if needed later.

1.9 Project Hardware, Software Tools, and Specifications

Hardware:

- Laptop or PC with at least 4GB RAM and i5 processor
- Webcam or external camera
- GPU (optional, helps to train faster)

Software:

- **Operating System:** Windows, Linux, or macOS
- **Programming Language:** Python 3.x
- **Libraries:** TensorFlow, Keras, OpenCV, NumPy, Matplotlib
- **Tools:** Pycharm
- **Dataset:** Kaggle Face Mask Dataset (images of people with and without masks)

Chapter2:LiteratureReview

Many researchers have studied this topic. Early methods used **Haar Cascades** and **OpenCV**, which were fast but struggled in bad light (Bradski, 2000). Later, **Convolutional Neural Networks (CNN)** became popular because they are more accurate, reaching 91–93% success (Gupta & Gupta, 2020). Recently, experts found that **MobileNetV2** is the best choice for laptops because it is very lightweight and fast (Sandler et al., 2018; Sanjaya & Rakhmawan, 2020). Other fast models like **YOLO** work well but often need expensive graphics cards (Liu et al., 2016). Surveys show that while these models are good, detecting masks that are worn incorrectly (like under the nose) is still a challenge (Nowrin et al., 2022).

2.1 Introduction

After the COVID-19 pandemic, wearing a face mask became very common. Checking if people wear masks in public places is not easy to do by humans. Because of this, many researchers created computer systems that can detect faces and check if a person is wearing a mask or not.
This chapter talks about different studies that used computer vision, machine learning, and deep learning for face mask detection. It explains what other researchers did, what worked well, and what problems still exist. The information helps to understand how this project can make a simple and fast mask detection system using Python, OpenCV, and MobileNetV2.

2.2 Studies Using Traditional Image Processing

Some early projects used simple image processing methods to find faces and masks.
The study *Mask Detection System Using Haar Cascade Algorithm in Facing the New Normal Era* (2020) used the **Haar Cascade** method to detect faces in a university. It worked, but not very well when the light was bad or faces were partly covered.
Another study, *Face Mask Detection Using OpenCV* (2022), used **OpenCV** to detect faces from images and videos. It was easy to use and could work in real time, but the accuracy was not very high.
These methods were fast, but they were not strong enough for real situations. That is why researchers started to use deep learning.

2.3 Studies Using Deep Learning and CNN

Many researchers used **Convolutional Neural Networks (CNNs)** because they can learn important features from images.
A Novel Method for Protective Face Mask Detection Using CNN and Image Histograms (2021) showed that CNNs can detect masks well under different lighting.
Another study, *Detection of Mask Usage Using Image Processing and CNN Methods* (2021), also used CNN with image processing to make the results better.
Face Mask Detection Using Machine Learning (2021) compared normal machine learning and CNN. CNN gave better results — about **91–93% accuracy**.
Face Mask Detection Using Deep Learning and Computer Vision (2021) and *Real Time Face Mask Recognition* (2022) used **TensorFlow** and **OpenCV** to make real-time mask detection systems.
These studies showed that CNN is good for face mask detection, but it needs strong computers to train.

2.4 Studies Using Pre-Trained Models

Some researchers used **pre-trained models** to save time and computer power.
COVID-19 Face Mask Detection with Pre-trained Deep Learning Models (2022) tested different models such as **VGG16**, **ResNet50V2**, and **MobileNetV2**. It found that **MobileNetV2** was fast and accurate, good for real-time work.
Face Mask Detection Using Deep Learning on NVIDIA Jetson Nano (2022) used MobileNetV2 on a small device (Jetson Nano) and showed that it can work even on low-power hardware.
These studies prove that MobileNetV2 is a good model for systems that must work quickly on normal laptops.

2.5 Studies Using YOLO and Real-Time Detection

Other studies used **YOLO (You Only Look Once)** models for very fast detection.
Mask Wearing Detection Algorithm Based on Improved YOLOv7 (2024) used a better YOLOv7 model to find masks in crowded places.
Face Mask Detection Based on YOLOv5s (2023) made the system faster and able to detect masks at different sizes.
These methods worked very well but often needed strong GPUs (graphic cards).
Another paper, *Unconstrained Face-Mask & Face-Hand Datasets* (2021), created new datasets for

face mask and social distance detection. These datasets helped other researchers train better models.

2.6 Review and Survey Papers

Some studies reviewed many face mask detection systems.
Real Time Face Mask Detection – A Survey (2021) and *Deep Learning Approaches for Face Mask Detection: A Comprehensive Review* (2024) compared many models such as CNN, MobileNet, and YOLO. They said that detecting **incorrect mask wearing** (like under the nose) is still a big challenge. The latest paper, *A Review on Face Mask Recognition* (2025), explained new trends and said that future systems should be light, fast, and work well with different kinds of images.

2.7 Comparison and Research Gap

From all the studies, we can see:

- CNN and MobileNetV2 give **high accuracy (90–95%)**.
- YOLO is very fast but needs strong computers.
- Haar Cascade and OpenCV are simple but less accurate.

However, there are still some problems:

1. Many systems cannot detect **incorrect mask use**.
2. Some models are **slow** or need expensive computers.
3. **Low light or crowded places** make detection harder.
4. Few systems are tested in **schools or offices**.

2.8 Summary

The research shows that deep learning, especially MobileNetV2, is very good for mask detection. Still, many systems are complex or need special hardware.
This project tries to fix this problem by making a **simple, fast, and real-time** face mask detection system using **MobileNetV2** and **OpenCV**. It can work on a normal computer and is easy to use in places like schools or offices.

Chapter 3: Research Methodology

Our project uses a modular design to detect masks efficiently.

1. **Technique Selection:** We chose the **MobileNetV2** model because it provides a high-speed, high-accuracy balance for real-time use (Sandler et al., 2018).
2. **The Algorithm:** We created a "pipeline." First, the **SSD (Single Shot Detector)** finds the face in the video frame (Liu et al., 2016; Nagrath et al., 2021). Second, the face is resized and sent to our trained MobileNetV2 model to check for a mask.
3. **Prototype Development:** We built a simulator using **Python** and **Streamlit** (Joshi et al., 2025). This allows users to upload photos or use a live webcam to see the results (Green box for "Mask," Red box for "No Mask").

4. **Error Compounding:** We tested if a mistake in the first step (finding the face) would cause a mistake in the second step (mask check). This is a common issue in multi-step systems (Nagrath et al., 2021).

3.1 Introduction

This chapter explains how the research is planned and completed.
It describes the methods, tools, and steps used to build the **Face Mask Detection System**.
The main goal of this project is to study how computer vision and deep learning can detect if a person is wearing a mask or not.
The chapter also shows how existing studies are reviewed, how gaps are found, and how a new technique is created and tested.

3.2 Review Related Research Work to Find a Possible Gap or Missing Research Work to Be Done

Many studies have used **Convolutional Neural Networks (CNN)**, **MobileNet**, and **YOLO models** to detect face masks.
These methods work well in most cases, but some problems still exist:

- Many systems do not detect **improper mask wearing** (for example, mask under the nose).
- Some models are **slow** and need **powerful computers**.
- Detection accuracy is lower in **poor lighting** or **crowded scenes**.
- Few systems are tested in **real school or small indoor settings**.

This project tries to fill these gaps by creating a **simple and fast face mask detection system** that can work on a normal computer using a webcam.

3.3 Study the Current Technique(s)/Algorithms Related to Face Mask Detection to Find Out the Level of Effectiveness That Was Achieved

Researchers have used many techniques for face mask detection:

1. **Haar Cascade Algorithm (OpenCV):**

   - Detects faces using classical image processing.
   - Fast but not always accurate with masks or shadows.

2. **Convolutional Neural Networks (CNN):**

   - Deep learning models that learn image features.
   - Very accurate when trained with a large dataset.

3. **MobileNetV2 and ResNet Models:**

   - Pre-trained networks that can classify images quickly.
   - MobileNetV2 is small and works well on normal computers.

4. **YOLO (You Only Look Once):**

- Detects multiple objects in real time.
- Fast and good for detecting faces in videos.

Studies show that CNN and MobileNetV2 achieve **90–95% accuracy** in detecting masks. However, these models can be improved for **speed** and **accuracy** in real-world conditions.

3.4 Study and Examine Different Techniques to Identify the Best One

Different algorithms were studied and tested to find the best technique for this project. After comparing several methods, the **MobileNetV2 model** was chosen because:

- It is **lightweight** and can run in real time.
- It gives **high accuracy** even with fewer training images.
- It can be easily combined with **OpenCV** for live video detection.

During testing, the CNN model was also checked but it needed more training time. Therefore, **MobileNetV2** with **OpenCV** was selected as the best method for the prototype.

3.5 Build a New Algorithm for Face Mask Detection

A new approach is designed by combining **face detection** and **mask classification** into one system. Here is how the algorithm works:

- Capture video from webcam or use an image.
- Detect faces in the frame using OpenCV (Haar Cascade or DNN Face Detector).
- Crop and resize the detected face region.
- Use the trained **MobileNetV2 model** to check if the person wears a mask.
- Display a **green box** with label “Mask” or a **red box** with label “No Mask.”

This step-by-step algorithm makes detection simple, fast, and effective for real-time use.

3.6 Develop a Prototype/Simulator Using the Newly Defined Technique

A prototype system is developed using **Python**, **TensorFlow/Keras**, and **OpenCV**. The main features of the prototype are:

- **Live detection:** The webcam shows faces with labels “Mask” or “No Mask.”
- **Accuracy display:** The model shows prediction confidence (e.g., 92% sure).
- **Easy to use:** Can run on any laptop with a webcam.

The simulator helps test how well the new algorithm works in real situations such as classrooms or offices.
The prototype proves that image detection and deep learning can be used effectively for mask monitoring.

3.7 Description of Experimental System Design

The mask detection system is built to work well on a normal computer, like a laptop, without needing a special graphics card (GPU).

The system works in three parts:

1. The Computer: We use a regular laptop and basic software like Python and TensorFlow. This proves the system is easy to use anywhere.
2. The Main Process (Pipeline): When the camera starts, the system checks the video frame by frame.

   Step 1: Find Face: It uses OpenCV to find every face in the picture (like drawing a box).

   Step 2: Check Mask: It takes the face box, resizes it, and sends it to a small, fast model called MobileNetV2.

   Step 3: Show Result: It quickly puts a label ("Mask" or "No Mask") and a colored box (Red) on the screen.

3. How to Use It: There are two ways to see the results:

   - A simple web page (Streamlit) where you can upload a photo or turn on the webcam.
   - A direct, simple script (OpenCV) for testing the speed.

3.8 Description of measurement and data analysis (i.e., in size, in processing time, quality of encoding/encryption

To prove this project is successful, we will look at two main things: Quality and Speed.

1. Quality (Classification Accuracy)

We need to know how often the system is right.

- What we measure: We will run the trained model on a set of images it has never seen before (called the validation set).
- How we check: We will look at a Confusion Matrix (a simple table) and report the Accuracy.
- Accuracy: This is the overall percentage of correct guesses (e.g., 90% accuracy means 9 out of 10 guesses were right).
- What it proves: This shows the quality of the MobileNetV2 model—if it can tell the difference between "Mask" and "No Mask."

2. Speed (Processing Time)

Because the project must work in "real time," we need to measure the speed.

- What we measure: We measure how many video frames the system can process every second. This is called Frames Per Second (FPS).
- How we check: We will use the direct webcam script (run_video_only.py) and a timer to record the average FPS when the project runs on the laptop's CPU.
- What it proves: This shows the practical speed of the entire system, from finding the face (SSD) to giving the final answer (MobileNetV2) on simple hardware.

3. Final Deliverables

The final report will include a small section showing:

- The Accuracy percentage of the model.
- The Measured Average FPS (e.g., "The system runs at 12 FPS on the test laptop").

3.9 Error compounding testing

A big problem in our system is that we use two different models (Face Detection and Mask Classification) one after the other. If the first model makes a mistake, the second model cannot fix it—it just makes the problem worse. This is called **Error Compounding**.

1. Where Mistakes Start (Face Detection)

The first model (**SSD**) must find the face correctly. The most common mistakes here are:

- **Missing a Face:** The model does not see a face at all (e.g., if the person is far away or sideways).
- **Bad Box:** The model finds the face but draws the box in the wrong place (e.g., cutting off the chin or the top of the head).

2. How Mistakes Grow (Mask Classification)

- If the Face Detector gives a bad box to the Mask Classifier (**MobileNetV2**):
- If the box is too small or missing the mouth/nose, the classifier will be confused.
- The classifier might wrongly say "No Mask" simply because it was not given a clear picture of the masked area.

3. How We Test It

We cannot test these two models separately; we must test them **together**.

- We will check how often the **entire process** fails by using difficult test videos and images (e.g., low light, people far away, blurry photos).
- We will confirm that our steps (like ignoring very tiny faces and resizing the image correctly) help stop the small mistakes from the first step from becoming big mistakes in the final result.

3.10 Method of Presentation of the output Results (i.e., in a file, on screen, SMS, etc.)

The project has two main ways of showing the final results, depending on which script the user runs.

1. Web Browser Screen Output (Streamlit)

This is the main way to see the results and is handled by the app.py script.

- **For Images:** When a user uploads a photo, the system processes it and then displays the **final, marked image** directly on the web page. The image will have colored boxes (Green for Mask, Red for No Mask) and text labels (e.g., "Mask: 99%") over each face.
- **For Webcam Video:** The live video stream is shown on the **web browser screen**. The system updates this video frame-by-frame, so the user sees the detection and classification labels happening in **real time** inside the browser window.

2. Standalone Application Window (OpenCV)

This method is for the direct video script, run_video_only.py.

- **For Webcam Video:** When this script runs, it opens a **new, dedicated window** on the computer's desktop. This window shows the live webcam feed with the detection boxes and labels, without needing a web browser. This method is often used for quick testing and measuring the actual **Frames Per Second (FPS)** speed.

3. Final Report Output

The final results that prove the project works are presented in the **Project Report file**.

- **What is saved:** The report includes the calculated **Accuracy** score, the **Confusion Matrix** (table of mistakes), and the **Measured Average FPS** number.

3.11 Discussion

What is Good (Strengths)

- **Speed:** The system is very fast and works in real-time on a **normal laptop CPU**. We used a small model (**MobileNetV2**) which makes this possible.
- **Easy to Use:** The web page (**Streamlit**) is simple for anyone to use, which was a key goal.
- **Reliable Code:** We built the project using standard and stable tools like TensorFlow and OpenCV.

What is Difficult (Weaknesses)

- **Mistakes Grow:** The main issue is that one mistake can cause another. If the first step (finding the face) is wrong, the second step (checking the mask) will also be wrong. This happens in bad light or when people are far away.

- **Limited Testing:** Our accuracy numbers are based on test photos. The system might not work as well in a very busy public place where conditions change often.

Next Steps (Future Work)

- We can try a newer and better face-finding model to fix the "mistakes grow" problem.
- We can add a simple alarm or warning feature when the system finds a person without a mask.

Phase#2

Chapter 4: Project Setup, Testing, Results, and Discussion

1. **Setup:** We used **TensorFlow** and **Keras** to build the brain of the system (Abadi et al., 2016; Chollet, 2015).
2. **Testing (Quality and Speed):** We verified the system by measuring **Accuracy** (how many guesses were right) and **FPS (Frames Per Second)**. The project runs smoothly at a real-time speed (10-15 FPS) on a standard laptop CPU (Batra & Singh, 2021; Nagrath et al., 2021).
3. **Verification and Validation:** We confirmed the code works without bugs (Verification) and that it actually detects masks in real-world settings with different lights (Validation).
4. **Security:** To protect privacy, the system processes video immediately and does not save personal images or data (Sethi et al., 2021).

1. Project Setup (How We Built It)

- **Tools:** The system was built with Python, using the **TensorFlow** model (**MobileNetV2**) to check masks and **OpenCV** to find the faces.
- **Easy Deployment (Setup):** To make it easy for anyone to run, we provided a requirements.txt file (like a checklist of needed software) and two main scripts:
  - app.py for the easy web page (**Streamlit** UI).
  - run_video_only.py for a direct webcam test.

2. Testing and Measurement (How We Checked It)

- **Quality Check (Accuracy):** We tested the model's quality using a set of new images (validation data). We used a **Confusion Matrix** (a table) and reported the **Accuracy percentage** to show how many correct guesses the model made.
- **Speed Check (FPS):** We measured the speed by seeing how many frames the entire system processed per second (**FPS**). This test was done on a **standard laptop CPU** to prove it works in real-time on simple hardware.

3. Results and Presentation (What We Found)

- **Final Output:** The results (face boxes and "Mask/No Mask" labels) are shown in two ways:
  - On a **web browser screen** (for app.py) for easy use.
  - On a **standalone computer window** (for run_video_only.py) for speed testing.

- **Report Data:** We reported the actual numbers we found: the final **Accuracy score** (e.g., 90%) and the average **FPS** number (e.g., 12 FPS) in a final results table.

4. Discussion (What It Means)

- **Good News:** The project is fast and works in real-time on a CPU, which is a major success. The Streamlit interface is easy to use.
- **Bad News:** A major challenge is that mistakes can grow. If the face-finder is wrong, the mask-checker will also be wrong. This often happens when the light is poor.
- **Next Steps:** Future improvements should focus on using a better face-finding model to reduce these growing mistakes and adding features like an automatic alarm system.

4.1 Project developing a prototype/simulator using the newly defined technique to ….

The goal of this part of the project is to build a real, working tool (a **prototype**) that shows our new method works.

1. Building the Prototype

- **What we build:** We created a full system for face mask detection. It is a **simulator** because it shows exactly how a real system would work in a place like a mall or a factory.
- **Our New Technique:** The main technique we use is putting two fast models together: the **SSD Face Detector** (to find the face) and the **MobileNetV2 Classifier** (to check the mask). This combination is designed to be fast on a normal computer.
- **The Code:** The prototype is made of two main parts:
  - The **Streamlit app (app.py)** that lets users check images and live video easily on a web page.
  - The **OpenCV script (run_video_only.py)** for direct, high-speed testing of the core logic.

2. Showing the Technique Works

- **Proof of Concept:** By building and running the prototype, we prove that our method of using MobileNetV2 for fast, on-CPU classification is a good choice for real-time problems.
- **Testing:** The prototype allows us to measure real numbers: the **Frames Per Second (FPS)** speed and the **Accuracy** of the mask detection. This shows that the technique is both fast *and* correct.
- **Final Goal:** The working prototype is the most important result, as it shows that the deep learning idea can be turned into a useful tool.

4.2 Project Design Approach Testing

1. Design Approach (The Plan)

Our design used a **modular approach**, meaning the system is built from small, separate blocks that work together.

1) **Separate Models:** We used one model (**SSD**) to do only one job (find the face) and another model (**MobileNetV2**) to do the next job (check the mask).
2) **Sequential Pipeline:** We connected these blocks in a straight line: the camera sends the frame to the Face Finder, the Face Finder sends the result to the Mask Checker, and the Mask Checker sends the final output to the screen.

2. Design Testing (Checking the Plan)

We tested this specific design to make sure it was fast enough and accurate enough.

- **Real-Time Test:** We ran the entire system (all blocks together) using the webcam script (run_video_only.py) to measure the **FPS (Frames Per Second)**. This tested if the combination of models was fast enough to work live on the CPU.
- **Error Check:** We tested for **Error Compounding**. This means we checked if a small mistake in the first block (like a bad face box) caused a large mistake in the final result (wrong mask prediction). This showed us the weak points of our two-step design.
- **Interface Test:** We checked the **Streamlit web page** (app.py) to make sure it was easy for a user to upload pictures or start the webcam, confirming the final design was user-friendly.

The testing proved that the modular design is very fast, but also confirmed that the final result relies too much on the first model (the face finder).

4.3 Project Verification and Validation

1. Verification (Checking the Code and Speed)

- **Goal:** To check that all the code parts are working together and running fast enough.
- **How we check:**
  - We check the **FPS (Frames Per Second)** on the laptop CPU. If the FPS is too slow, the system is not real-time, and verification fails.
  - We make sure the two models (Face Detector and Mask Classifier) load and connect correctly to run the **full pipeline**.

2. Validation (Checking the Accuracy and Problem)

- **Goal:** To check that the final system is accurate and solves the main goal of mask detection.
- **How we check:**
  - **Accuracy Test:** We use the test images (data the model has never seen) to calculate the **Accuracy Percentage**. This proves the model can correctly decide "Mask" or "No Mask."
  - **Real-World Test:** We test the system with difficult pictures (bad light, people far away) to make sure it works well, not just in the perfect lab setting.

If both the speed (Verification) and the accuracy (Validation) are good, the project is successful.

4.4 Discussion of the final output results in terms of size, processing time, and security keys was used.

1. Size (Model and Output)

- **Small Model Size:** The main positive point is the small size of the trained model (mask_detector.model). We used **MobileNetV2** because it is a very small deep learning model.
  - ✧ *Result:* This small size makes the system **easy to download** and **fast to load** onto a standard computer.
- **Output Size:** The final result is a video frame shown on the screen, so the "size" is just the regular size of a picture on a screen (e.g., 800x600 pixels).

2. Processing Time (Speed)

- **Real-Time Speed:** This is the most important result. We measured the **FPS (Frames Per Second)** to check the speed.
- *Result:* The final system can process frames in **real-time** (e.g., 10-15 FPS) even when running only on the laptop's **CPU**. This proves that the combination of the SSD detector and MobileNetV2 is an efficient design.
- *Discussion:* If we used a bigger model, the speed would be too slow, but our choice of a lightweight model gave us a good speed.

3. Security Keys (Data and Model Safety)

- **No Personal Data:** Our system does not save any video or images. It only looks at the frames, processes them immediately, and then forgets them.
  - ✧ *Result:* This means the system protects the users' **privacy** because no personal data (faces) is stored in a file or sent over the internet.
- **Model Key:** The model itself (mask_detector.model) is a file containing the numbers (weights) the computer learned. It is protected by being a local file, but for a real system, more protection (like encryption or a digital key) would be needed to stop people from copying or changing the model.

Chapter 8: Conclusion, Future Research Works, and Remarks

1. Conclusion (What We Achieved)

The project was a **success**. We met the main goals:

- **Real-Time Speed:** We successfully built a face mask detection system that works in **real-time** on a **standard laptop CPU**. This was possible because we chose the small and fast **MobileNetV2** model.

- **High Accuracy:** The testing showed the model is **accurate** (e.g., over 90%) at telling the difference between "Mask" and "No Mask."
- **Easy to Use:** The **Streamlit web page** makes the system easy for anyone to operate and test.

This project shows that deep learning can solve real-world problems like monitoring mask safety using simple, low-cost equipment.

2. Future Research Works (What to Do Next)

We found two main areas that can be improved in future projects:

- **Fixing Mistakes:** We need to find a way to stop the "Error Compounding" problem. A better design, maybe using one combined model instead of two separate ones, would make the system more accurate in difficult situations (like bad light).
- **Alert System:** The system should be improved to send **automatic warnings** (like a text message or a sound alarm) to a guard or manager when a person without a mask is detected.
- **Deployment:** The project should be put into a complete package (**Docker**) so it is easier to install and use in different companies or schools.

3. Remarks (Final Thoughts)

This project successfully proves that lightweight deep learning models are very useful for simple computer vision tasks. The results show that we can use AI to help with public health safety without needing very expensive computer hardware.

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