

# Comparative Analysis: Traditional Machine Learning vs. CNN-Based Mask Detection

## 1 Introduction

This document presents a **comprehensive comparison** of the accuracy achieved by different models in both **Part A (Traditional ML Models)** and **Part B (CNN-Based Deep Learning Models)** for the **mask detection task**. We analyze the **best-performing models**, **hyperparameters**, and key insights that explain the differences in performance.

## 2 Steps to Run

You can execute the following Python files and Jupyter notebooks in Part A and Part B:

### 2.1 Part A:

- **Python Files:**
  - `feature_extraction.py`
  - `Colab_USAGE_ML.ipynb` (for training in Colab)
  - `main.ipynb` (for model evaluation)

### 2.2 Part B:

- **Python Files:**
  - `Colab_USAGE_CNN.ipynb` (for training in Colab)
  - `main.ipynb` (for model evaluation)

**Note:** Do not run the Colab files locally; they are designed for execution in Google Colab, which provides the necessary GPU resources.

### 3 Directory Structure

```
C:.\nCOMPARISON_README.MD\nA_Binary_Classification_Using_Handcrafted_Features_and_ML_Classifiers\n  A_README.MD\n  enhanced_features\n  saved_models\n  plots\nB_Binary_Classification_Using_CNN\n  B_README.MD\n  Advanced_Analysis\n    snapshots\n    histories\n    models\n    plots\n  Normal_Analysis\n    cnn_models\n    cnn_processed_data
```

### 4 Overview of Model Performance

#### 4.1 Part A: Traditional Machine Learning Models

Model	Validation Accuracy
SVM	<b>93.87%</b>
MLP	93.25%
XGBoost	92.64%
RandomForest	90.06%

Table 1: Performance of Traditional ML Models

#### 4.2 Part B: CNN-Based Deep Learning Models

##### Normal CNN Models

Model	Validation Accuracy
ReLU + Adam	<b>96.70%</b>
Tanh + Adam	96.58%
ReLU + SGD	90.84%

Table 2: Performance of Normal CNN Models

##### Advanced CNN Models

Model	Validation Accuracy
Baseline CNN	<b>97.68%</b>
VGG-like CNN	96.09%
ResNet-like CNN	95.48%
MobileNet	<b>43.83%</b> (failed)

Table 3: Performance of Advanced CNN Models

## 5 Best Model in Each Category

- **Traditional ML Winner:** SVM (**93.87%**)
- **CNN Normal Winner:** ReLU + Adam (**96.70%**)
- **CNN Advanced Winner:** Baseline CNN (**97.68%**) (**Final Winner**)

## 6 Hyperparameters Comparison

Approach	Feature Extraction	Architecture	Optimizer	Epochs	Batch Size	Best Accuracy
Part A (ML)	HOG, LBP, Color Hist.	SVM, MLP, XGBoost	N/A	N/A	N/A	<b>93.87%</b> (SVM)
Part B Normal	None (Raw Images)	Simple CNN	Adam/SGD	25	64	<b>96.70%</b> (ReLU + Adam)
Part B Advanced	None (Raw Images)	Deeper CNNs	Adam	25	64	<b>97.68%</b> (Baseline CNN)

Table 4: Comparison of Hyperparameters

## 7 Key Observations

### 7.1 Why Did CNNs Outperform Traditional ML?

- CNNs **learn features automatically** while ML models require hand-crafted feature extraction.
- CNNs **train end-to-end on raw images**.
- Deeper architectures provide **richer feature representations**.

### 7.2 Why Did Some CNNs Perform Worse?

- **MobileNet failed** due to missing pretrained weights.
- **ReLU + SGD (90.84%)** had slow convergence.
- **VGG-like and ResNet-like** had **slight overfitting**.

<b>Metric</b>	<b>Traditional ML</b>	<b>CNN Normal</b>	<b>CNN Advanced</b>
Best Accuracy	93.87% (SVM)	96.70% (ReLU + Adam)	<b>97.68% (Baseline CNN)</b>
Feature Extraction	Required	None (Learned)	None (Learned)
Training Time	Fast	Moderate	High
Generalization	Moderate	High	Very High
Computational Cost	Low	Medium	High

Table 5: Final Comparison of Approaches

## 8 Conclusion: Which Approach is Better?

**Final Verdict:** CNNs are superior, with the best model being Baseline CNN (97.68%).