# Analysis Report

## Introduction

The COVID-19 pandemic highlighted the critical role of face masks in public health safety. Our project aims to develop a machine learning model to detect face masks in images, identifying compliance with health guidelines. We leverage the Kaggle "Face Mask Detection" dataset, featuring 853 images and 4,099 annotated faces categorized as "with mask," "without mask," or "mask worn incorrectly." This diverse dataset enables the creation of a model adept at recognizing mask usage across different scenarios.

## Methodology

## Our methodology encompasses three experiments, each utilizing different models to detect face mask use in images.

1. Supervised Learning: We developed a custom CNN to classify images based on mask usage, experimenting with architecture, layer depth, and regularization techniques to enhance performance and generalization.

2. Unsupervised Learning: We used a GAN for data augmentation, creating synthetic images to enrich our dataset. Transfer learning was also applied for feature extraction, enhancing our model's ability to detect mask usage.

3. State-of-the-Art Models: We employed the VGG16 model, known for its image classification prowess, using it both from scratch and with transfer learning to improve detection accuracy and efficiency.

The efficacy of each approach was measured through accuracy, precision, recall, and F1-score, providing a comprehensive comparison of their performance in face mask detection.

## Results

This section outlines the performance evaluation of our models across the three experiments conducted: Supervised Learning, Unsupervised Learning (with a focus on data augmentation and feature extraction), and the application of the State-of-the-Art VGG16 model. We employ several key metrics for evaluation, including accuracy, precision, recall, and F1-score, to provide a comprehensive analysis of each model's effectiveness in detecting face masks in images.

**1. Supervised Learning Experiment**

In our exploration of Supervised Learning, we meticulously designed a custom Convolutional Neural Network (CNN) by experimenting with various configurations. The ultimate architecture was fine-tuned to include a specific number of layers, neurons per layer, and kernel size to optimally address our problem statement. The strategic integration of dropout and batch normalization played a crucial role in enhancing the model's performance, notably minimizing overfitting.

* **Accuracy: 91.81%**
* **Precision: 45.91%**
* **Recall: 50.00%**
* **F1-Score: 47.87%**

The performance metrics reveal that while our custom CNN model achieves high accuracy, its precision and recall suggest there is room for improvement in accurately distinguishing between the different mask-wearing conditions. This outcome prompts further investigation into optimizing the model's ability to generalize across varied real-world scenarios, highlighting the necessity for balanced data representation and possibly more sophisticated feature extraction techniques to improve precision and recall.

**2. Unsupervised Learning Experiment**

Our Unsupervised Learning experiment capitalized on the innovative use of a Generative Adversarial Network (GAN) to create synthetic images for data augmentation. This approach, coupled with the strategic employment of a pre-trained model for nuanced feature extraction via transfer learning, significantly enhanced our model's face mask detection capabilities.

* **Accuracy (with GAN augmentation): 94%**
* **Precision (with GAN augmentation): 100%**
* **Recall (with GAN augmentation): 93%**
* **F1-Score (with GAN augmentation): 96%**

The inclusion of GAN-generated images led to a notable improvement in our model's performance metrics, illustrating the profound impact of data augmentation on detection accuracy and reliability. This underscores the effectiveness of using synthetic data to enrich training datasets, especially in scenarios where real-world data may be limited or imbalanced. The results highlight the potential of combining unsupervised learning techniques with transfer learning to significantly boost model performance, opening up avenues for further research into optimizing these methods for even greater efficacy.

**3. State-of-the-Art Models Experiment**

In this phase, we explored the VGG16 architecture's potential, applying it in two distinct manners: training from scratch and adapting via transfer learning. The outcomes were as follows:

* **VGG16 (from scratch)**
  + **Accuracy: 91.23%**
  + **Precision: 0.63**
  + **Recall: 0.53**
  + **F1-Score: 0.54**
* **VGG16 (with transfer learning)**
  + **Accuracy: 97.66%**
  + **Precision: 0.95**
  + **Recall: 0.89**
  + **F1-Score: 0.92**

Transfer learning significantly surpassed the scratch-trained model, underscoring the advantages of utilizing pre-trained models for intricate tasks such as face mask detection. The remarkable improvement in accuracy and F1-score with transfer learning demonstrates its efficiency, especially in scenarios with limited data or computational resources.

**Discussion**

Our comparative analysis reveals that while the custom CNN model demonstrated a solid accuracy in the Supervised Learning experiment, its lower precision and recall hinted at the necessity for more intricate feature recognition and balanced datasets. The significant performance leap observed with the use of GAN-generated images in the Unsupervised Learning experiment highlighted the vital role of diverse training data. Furthermore, employing the VGG16 model via transfer learning showcased the most notable improvement, outshining the scratch-trained model and underscoring the efficiency of utilizing pre-trained models. The marked success of transfer learning and data augmentation across our experiments emphasizes their critical contribution to addressing the variability and enhancing the robustness of models in complex classification tasks.

**Conclusion**

This exploration into deep learning for face mask detection illustrates the transformative impact of transfer learning and data augmentation, with the VGG16 model applied via transfer learning emerging as the most effective approach. These methodologies significantly enhance model performance, suggesting future research should delve into refining these strategies and exploring new architectures to tackle the limitations of data diversity and computational resources. Our findings advocate for a continued emphasis on leveraging unsupervised learning and state-of-the-art models to push the boundaries of accuracy and practicality in public health applications.

## Contribution

**Chengqing Liu:** Implemented and analyzed state-of-the-art models, focusing on TensorFlow's pre-trained models and transfer learning.

**Faiyaz Muhammad:** Edited the project documentation and code, ensuring clarity and accuracy in the ReadMe file and script files.

**Le Bao Binh Hoang:** Developed the unsupervised learning model, focusing on data augmentation through generative models.

**Phuong Dinh:** Led the supervised learning experiment, creating and optimizing a custom CNN/RNN model for the project's task.