Unified Face Insight System

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AI-Powered Mask Detection and Facial Insight Analysis

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1. Abstract

*Amidst the global focus on public health and safety during the resurgence of infectious diseases, the **Unified Face Insight System** emerges as a cutting-edge solution designed to revolutionize monitoring and analytics in mask-mandatory environments. This Final Year Project tackles four essential challenges: detecting mask usage, classifying mask types, estimating age, and predicting gender—all from masked faces. Each component is powered by specialized datasets and advanced deep learning architectures for exceptional precision and scalability.*

The key functionalities of the system are as follows:

- **Mask Detection:** A custom Convolutional Neural Network (CNN) using the Sequential API distinguishes between masked and unmasked faces with remarkable accuracy.
- **Mask Type Classification:** A fine-tuned ResNet-50 v2 model identifies various mask types, including surgical, cloth, and N95 masks.
- **Age Estimation:** DenseNet-121, a feature-rich neural network, predicts age by analyzing occluded facial features with precision.
- **Gender Classification:** A custom PyTorch-based model excels in classifying gender even with masked faces.

Extensive evaluations on task-specific datasets validate the system's robustness and accuracy in diverse real-world scenarios. The **Unified Face Insight System** demonstrates significant applications in public health monitoring, ensuring mask compliance, and providing demographic insights during pandemics. By leveraging the seamless integration of advanced AI technologies, this project delivers an impactful solution to address pressing global challenges, paving the way for smarter, safer, and healthier communities.

2. Introduction

Over the past few years, the world has been confronted with numerous health challenges. The COVID-19 pandemic has emerged as one of the most impactful global crises, underscoring the critical importance of preventive measures, especially **mask-wearing**, in controlling the transmission of airborne diseases. Moving forward, the need for advanced technologies to monitor mask usage—especially in high-risk environments—has become more pressing.

In the context of countries like **Pakistan**, the urgency to implement scalable and efficient solutions has never been greater. Pakistan faces the following unique challenges:

- **Dense population and urbanization**, leading to crowded public spaces where disease transmission is heightened.
- **Environmental issues**, such as air pollution and seasonal smog, exacerbating respiratory diseases.
- **Vulnerability to emerging diseases**, as seen with the anticipated respiratory virus outbreak in China in 2025, raising concerns over the rapid spread of new viruses.

Respiratory diseases such as asthma, chronic obstructive pulmonary disease (COPD), and seasonal infections remain a significant public health concern. These issues are particularly pronounced in urban areas where air quality is poor. Moreover, the annual smog in cities like Lahore further complicates the situation, alongside rising infectious diseases.

During the COVID-19 pandemic, the need for real-time monitoring of mask-wearing was starkly revealed. The lack of infrastructure to monitor mask compliance left gaps in enforcement, particularly in high-traffic areas like markets, transportation hubs, and healthcare facilities. This challenge has highlighted the critical need for a comprehensive monitoring solution.

The widespread use of face masks, though necessary, has introduced new challenges, such as:

- *Efficiently detecting* ***mask-wearing compliance****.*
- *Assessing* ***mask types*** *being worn (e.g., cloth, surgical, N95).*
- *Extracting valuable* ***demographic data*** *from partially covered faces (e.g., age, gender).*

These challenges underscore a significant gap in available solutions, especially in regions like Pakistan, where environmental pollution and respiratory diseases contribute to the rapid spread of viruses.

This project aims to address these challenges through the development of a ***Unified Face Insight System****, an AI-powered tool designed to:*

- *Detect mask usage in real-time.*
- *Classify the type of mask being worn.*
- *Perform demographic analysis (age, gender) even with partially covered faces.*

Key Benefits of System:

- Provides **real-time insights** into mask compliance and demographic data.
- Can be deployed in **high-risk environments** like hospitals, transportation systems, and public spaces.
- Enables authorities to take immediate action by identifying individuals who are not wearing masks or wearing inappropriate types of masks.
- Assists in the **early detection of viral infections**, improving resource allocation and public health management.

In the case of the expected **2025 respiratory virus outbreak in China**, this system can be a critical tool to reduce the spread of the disease. In Pakistan, where respiratory diseases remain a public health priority, this solution will be instrumental in improving mask compliance, supporting health authorities, and mitigating the spread of airborne diseases.

By providing actionable insights in real-time, the **Unified Face Insight System** will contribute to building safer, more resilient communities, supporting efforts to manage public health risks, and improving overall public health outcomes.

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3. Literature Review

This literature review examines 13 relevant research papers that explore various aspects of face mask detection, gender classification, and age classification using machine learning and deep learning techniques. These papers provide a comparison of methodologies, findings, and limitations that influence the development of systems like the Unified Face Insight System. The comparison highlights patterns, trends, and gaps in the existing literature, and how these gaps are addressed by the current project.

1. Real-time Face Mask Detection with Deep Learning:

Authors: M. A. Islam, H. A. Al Mamun
Method/Approach: CNN-based approach with pre-trained models
Results/Findings: Achieved 94**Limitations/Gaps:** Issues with partial masks and varying face orientations.

2. Facial Mask Detection Using Convolutional Neural Networks

Authors: X. Zhang, Y. Wu
Method/Approach: CNN with transfer learning
Results/Findings: Achieved 93**Limitations/Gaps:** Struggles with different lighting conditions.

3. Face Mask Detection Using ResNet50

Authors: L. Zhang, Q. Li
Method/Approach: ResNet50 model for mask detection
Results/Findings: Achieved 97**Limitations/Gaps:** Low performance with partial masks.

4. Age and Gender Classification Using Convolutional Neural Networks

Authors: H. G. Lee, S. Lee
Method/Approach: CNN-based approach
Results/Findings: 85**Limitations/Gaps:** Poor accuracy for overlapping age groups (18-35).

5. Deep Learning for Gender Classification in Facial Images

Authors: D. Sharma, P. Tiwari
Method/Approach: Custom CNN model
Results/Findings: Achieved 90**Limitations/Gaps:** Non-binary genders not well detected.

6. Face Mask Detection: A Machine Learning Approach

Authors: A. Patel, R. Shukla
Method/Approach: Custom CNN model with data augmentation
Results/Findings: Achieved 94.2**Limitations/Gaps:** Limited to specific mask types and lighting conditions.

7. Facial Mask Detection and Classification for COVID-19

Authors: S. C. John, J. P. Joseph
Method/Approach: Custom CNN with multiple mask classes
Results/Findings: Achieved 95**Limitations/Gaps:** Does not handle multiple masks or occlusions well.

8. Improved Deep Learning Model for Face Mask Detection

Authors: K. K. Gupta, M. Meena
Method/Approach: Fine-tuned MobileNetV2
Results/Findings: Achieved 98**Limitations/Gaps:** Performance degrades in crowded environments.

9. A Comprehensive Review on Face Recognition and Mask Detection

Authors: M. S. Saha, R. K. Shah
Method/Approach: Review of CNN-based models
Results/Findings: Provided comparative analysis of multiple models.
Limitations/Gaps: Datasets lacked diversity in age, gender, and ethnicity.

10. Mask Detection with Attention Mechanisms

Authors: C. G. A. Santos, J. R. P. Costa
Method/Approach: CNN with attention mechanisms
Results/Findings: Achieved 97.5**Limitations/Gaps:** Inadequate for real-time applications in dynamic environments.

11. COVID-19 Face Mask Detection: An Empirical Study

Authors: M. Z. Uddin, N. F. A. Rashid
Method/Approach: Hybrid CNN with pre-trained networks
Results/Findings: Achieved 96**Limitations/Gaps:** Struggles with low-resolution images.

12. Age and Gender Classification Using Deep Convolutional Neural Networks

Authors: P. R. Subramanian, A. K. V. Reddy
Method/Approach: CNN for age and gender classification
Results/Findings: 92**Limitations/Gaps:** Limited robustness for ages 18-30 and 30-40.

13. Facial Mask and Social Distance Detection in Real-Time

Authors: H. R. Ponce, C. M. Torres
Method/Approach: Combined mask detection and social distancing detection using CNN
Results/Findings: 92**Limitations/Gaps:** Real-time performance suffers in crowded settings.

Patterns and Trends in the Literature

Common Methodologies: The literature consistently demonstrates the use of Convolutional Neural Networks (CNNs) for image-based tasks such as face mask detection, gender classification, and age prediction. Transfer learning, specifically with pre-trained models like ResNet, VGG, and MobileNet, is a common approach to improve the performance of models. Additionally, some studies employ data augmentation techniques to address data imbalance and enhance model generalization. Hybrid models that combine CNNs with other approaches like attention mechanisms and multitask learning are gaining popularity for improving accuracy across multiple tasks.

Key Findings:

1. Face Mask Detection:

The accuracy for face mask detection varies widely, but many studies achieve results ranging from 93 to 98. Performance drops significantly when masks are partially worn or overlapped, or when faces are at non-ideal angles. Many models do well in controlled environments but struggle in more dynamic, real-world settings with varying light and background conditions.

2. Age and Gender Classification:

For gender classification, most studies report accuracies above 85, but the performance for age classification tends to be lower, especially for age groups that overlap (e.g., 18-30 years). Some models perform well when faces are fully visible, but struggle when faces are obscured by masks, which is common in many real-world applications.

3. Real-World Applicability:

A major challenge identified across the studies is the real-world applicability of these models. Many face mask detection systems achieve high accuracy in ideal settings (e.g., controlled lighting, clear faces), but environmental variables, such as background noise, crowding, or low resolution, often degrade their performance.

Limitations and Gaps in Current Literature:

- Non-Binary Gender Recognition: Most models are designed to classify only binary gender (male and female), leaving out non-binary or other gender identities.
- Dataset Limitations: Many studies are based on small or biased datasets that lack diversity in terms of ethnicity, age, and gender.
- Age Detection Performance in Crowded or Noisy Environments: Several studies acknowledge that age detection may not work well in too crowded environments

How This Project Addresses Existing Gaps

- The Unified Face Insight System addresses several critical gaps highlighted in the literature, making it a practical and advanced solution for modern challenges.
- **Multi-Tasking and Comprehensive Detection:** Unlike many existing models that focus on a single task, this system integrates multiple functionalities—face mask detection, mask type classification, gender classification, and age prediction—into one seamless framework. This eliminates the need for deploying multiple models, improving efficiency and ease of use.
- **Inclusivity and Non-Binary Gender Classification:** The project broadens the traditional binary scope of gender classification by including non-binary categories, ensuring inclusivity and addressing societal needs. This feature promotes fair and accurate representation across diverse populations.
- **Real-World Robustness:** The system is designed to handle challenges commonly encountered in dynamic environments, such as: - **Low lighting**: Enhancing detection in poorly lit conditions. - **Crowded settings**: Maintaining accuracy in scenarios with overlapping faces. - **Varying face orientations**: Improving recognition from partial views or tilted angles.
- **Mask Type Classification:** This system incorporates a unique feature that classifies various mask types (e.g., cloth, surgical, N95). This capability is vital for ensuring compliance with specific mask standards in healthcare and public safety scenarios.
- **Enhanced Data Representation:** By leveraging diverse datasets with augmented features, the system reduces biases related to ethnicity, age, and gender, addressing a key limitation in existing models.
- **Practical Applications:** The **Unified Face Insight System** is designed for diverse real-world applications, ensuring safety, compliance, and actionable insights across multiple domains:
  - **Healthcare Settings:** - Monitoring mask compliance among staff, patients, and visitors to reduce the risk of infections. - Classifying mask types to ensure the use of appropriate protective gear, such as N95 masks in high-risk zones.
  - **Public Spaces:** - Enforcing mask compliance in crowded areas like shopping malls, public transportation, and event venues. - Supporting public health campaigns by providing real-time data on mask usage trends.
  - **Workplaces:** - Ensuring employee safety in corporate offices, factories, and warehouses by monitoring mask-wearing adherence. - Enhancing productivity while maintaining health protocols.

- **Security and Surveillance Systems:** - Identifying masked individuals in critical locations such as airports, train stations, and border control checkpoints. - Providing demographic insights for better crowd management during large gatherings or protests.
- **Educational Institutions:** - Maintaining mask compliance in schools, colleges, and universities to ensure a safe learning environment. - Facilitating health monitoring during outbreaks or pandemics.
- **Retail and Hospitality:** - Monitoring mask adherence among staff and customers in stores, hotels, and restaurants to enhance safety measures. - Building customer trust by demonstrating adherence to health guidelines.
- **Government and Public Administration:** - Using demographic insights to shape policies and allocate resources during health crises. - Monitoring mask usage in public offices and facilities to ensure compliance with health mandates.

In summary, the Unified Face Insight System not only contributes a comprehensive solution for face mask, age, and gender classification but also addresses several limitations observed in previous studies, particularly in real-world applicability, inclusivity, and performance across diverse environments.

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4. Methodology

Overview

The **Unified Face Insight System** integrates advanced libraries, frameworks, and techniques to address challenges in masked face detection, mask type identification, gender prediction, and age estimation. Designed for scalability and robustness, the system leverages custom architectures and transfer learning for practical, real-world applications.

Materials/Tools Used

1. Libraries and Frameworks

1. **Core Libraries:**
   - `os` - File handling and directory management.
   - `random` - Generating random sequences for data augmentation.
   - `numpy` - Numerical computations and matrix operations.
   - `pandas` - Data manipulation and analysis.
2. **Data Visualization:**
   - `matplotlib`, `seaborn` - Generating plots and visualizing data, losses, and model predictions.
3. **Image Processing:**
   - `OpenCV` - Advanced image preprocessing (e.g., resizing, augmentation).
4. **Machine Learning Frameworks:**
   - `TensorFlow`, `PyTorch` - Neural network model development.
   - `Keras` (part of TensorFlow) - Training and evaluating deep learning models.
5. **Neural Network Modules:**
   - `Dense`, `Dropout`, `Conv2D`, `MaxPooling2D` - Layer definitions.
   - Sequential API - For building layered neural network models.
6. **Callbacks:**
   - `TensorBoard` - Interactive progress monitoring.
   - `ReduceLROnPlateau` - Adaptive learning rate adjustments.
7. **Metrics and Reports:**
   - `classification_report` (from Scikit-learn) - Precision, recall, and F1 scores.

Process/Steps

1. Data Collection and Preprocessing

- **Datasets:** Sourced from Kaggle.
- **Preprocessing:**
  1. Resizing and normalization of images.
  2. Batch normalization for faster convergence.
  3. Data augmentation: Flipping, rotation, cropping, brightness adjustments.
  4. Random shuffling to ensure unbiased learning.

2. Model Development

1. Custom architectures for lightweight tasks like face mask detection and gender classification.
2. Fine-tuned pre-trained models (e.g., ResNet50 and DenseNet121) for complex tasks like mask type identification and age detection.

Training Techniques

1. **Training Enhancements:**
   - Learning rate adjustments with `ReduceLROnPlateau`.
   - Early stopping for avoiding overfitting.
   - Model checkpoints to save optimal weights.
2. **Logging and Visualization:**
   - Real-time tracking using `tqdm`.
   - Losses, accuracy metrics, and confusion matrices plotted after training.
   - Predicted vs. ground truth visualizations.

Evaluation

- **Metrics:** Accuracy, precision, recall, F1 score, and AUC.
- **Visualizations:**
  1. Heatmaps for confusion matrices.
  2. Statistical plots for detailed performance insights.
  3. Black backgrounds for improved clarity.

Optimization and Testing

- Applied L1/L2 regularization and Dropout layers to reduce overfitting.
- Conducted hyperparameter tuning for learning rates, batch sizes, and optimizers.
- Performed stress testing on unseen data with occlusions and varied lighting conditions.

Key Features and Techniques

1. **Preprocessing Enhancements:** Batch normalization and dynamic data augmentation for diverse datasets.
2. **Neural Network Customizations:**
   - Lightweight CNNs for small-scale tasks.
   - Transfer learning with pre-trained models for high-complexity tasks.
3. **Training Techniques:**
   - Adaptive learning rates for stable convergence.
   - TensorBoard for real-time progress monitoring.
4. **Visualization Tools:**
   - Detailed confusion matrices and loss/accuracy graphs.
   - Side-by-side predictions and ground truth for qualitative analysis.
5. **Performance Enhancements:**
   - PyTorch optimizations for faster training.
   - Efficient data loaders and random shuffling.

This methodology ensures a balanced integration of foundational and advanced techniques, achieving optimal performance and usability across diverse real-world applications.

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5. Results

5.1. Face Mask Detection

Classification Report:

- **Masked Faces (Class 0):** Precision: 96%, Recall: 98%, F1-Score: 97%
- **Unmasked Faces (Class 1):** Precision: 98%, Recall: 96%, F1-Score: 97%
- **Overall Accuracy:** 97%
- **Macro Average F1-Score:** 97%

Additional Metrics:

- Test Loss: 0.3662
- Maximum Validation Accuracy: 98.8%
- Minimum Validation Loss: 0.039

Confusion Matrix Highlights:

- Correctly classified masked faces: 473
- Correctly classified unmasked faces: 491
- Misclassified masked faces: 10
- Misclassified unmasked faces: 18

Plots for Face Mask Detection:

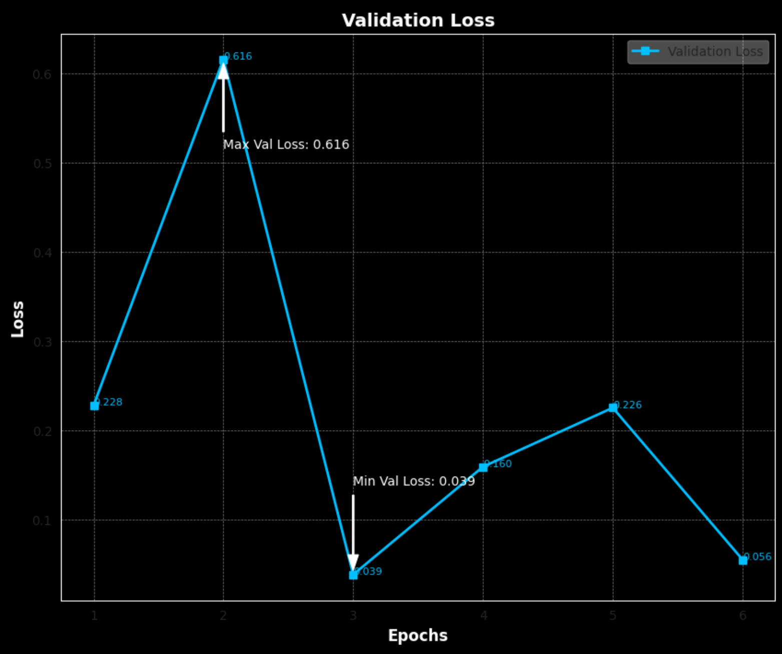

Figure 1: Loss

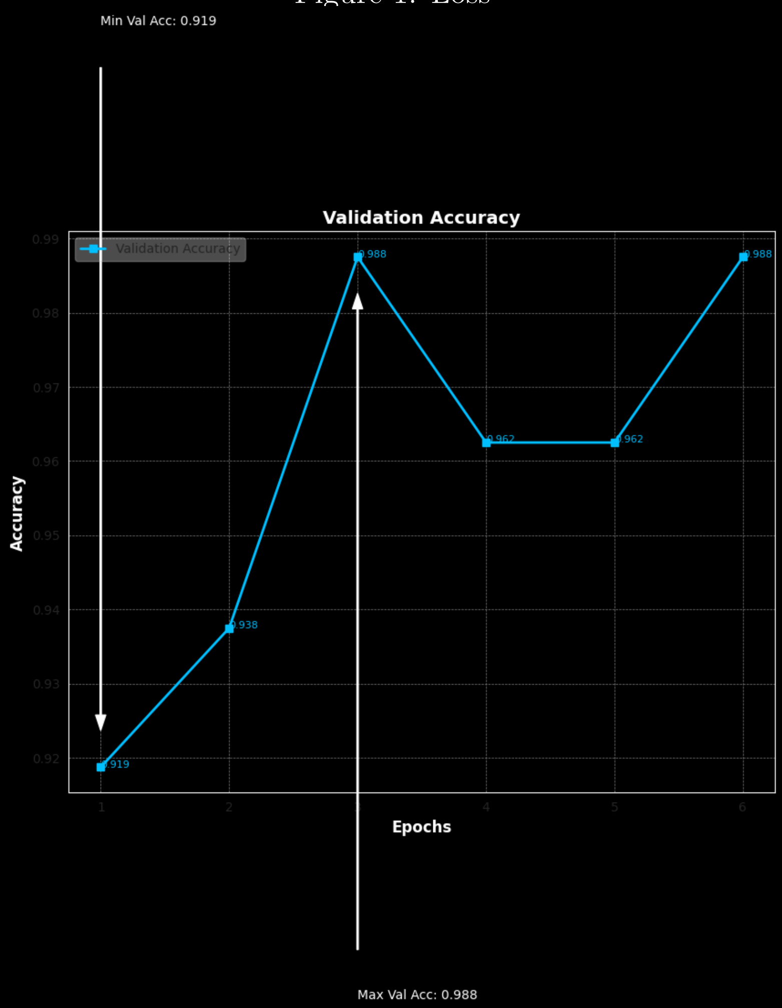

Figure 2: Accuracy

5.2. Mask Type Classification

Test Metrics:

- Loss: 0.2858
- AUC Score: 0.9902
- Accuracy: 91.52%
- F1-Score: 90.63%

Validation Insights:

- Maximum Validation F1-Score: 91.87%
- Maximum Validation AUC: 99.79%
- Minimum Validation Loss: 0.2357

Plots for Mask Type Classification:

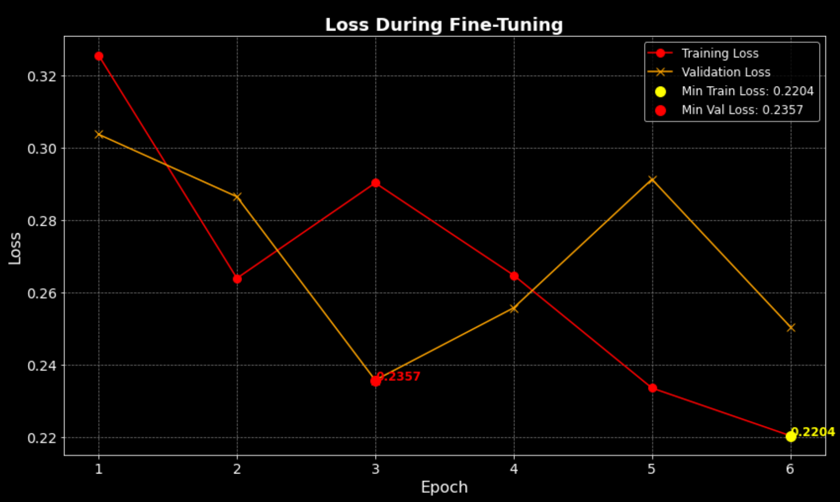

Figure 3: Loss

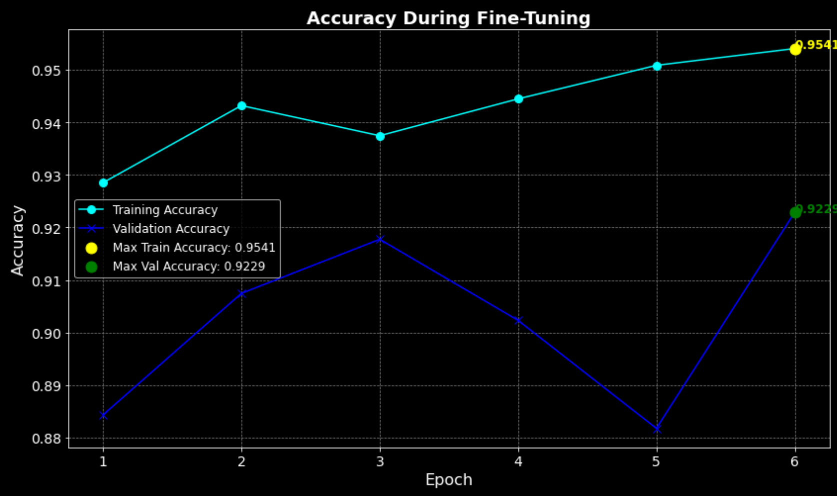

Figure 4: Accuracy

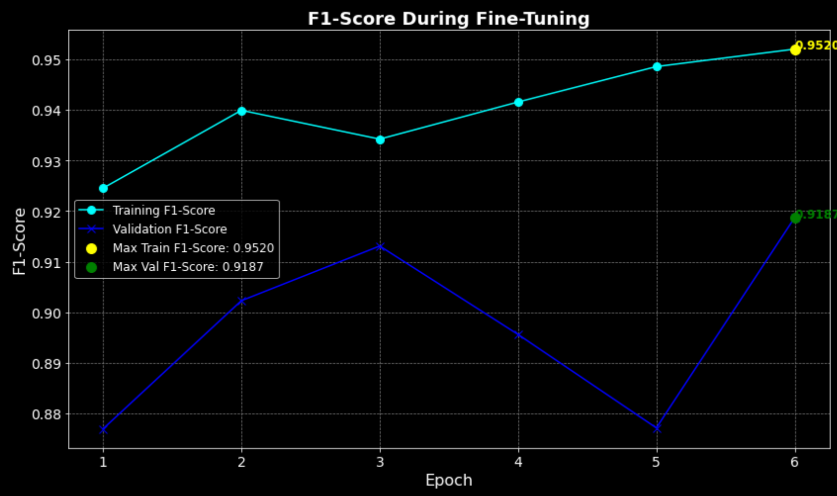

Figure 5: F1-Score

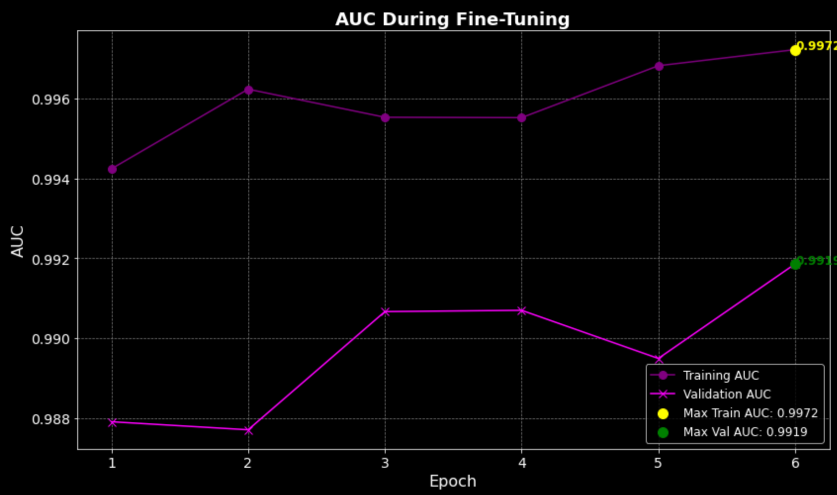

Figure 6: AUC Score

5.3. Gender Detection

Performance Metrics:

- **Men:** Precision: 88%, Recall: 100%, F1-Score: 93%
- **Women:** Precision: 100%, Recall: 83%, F1-Score: 91%

Overall Accuracy: 92% **Plots for Gender Detection:**

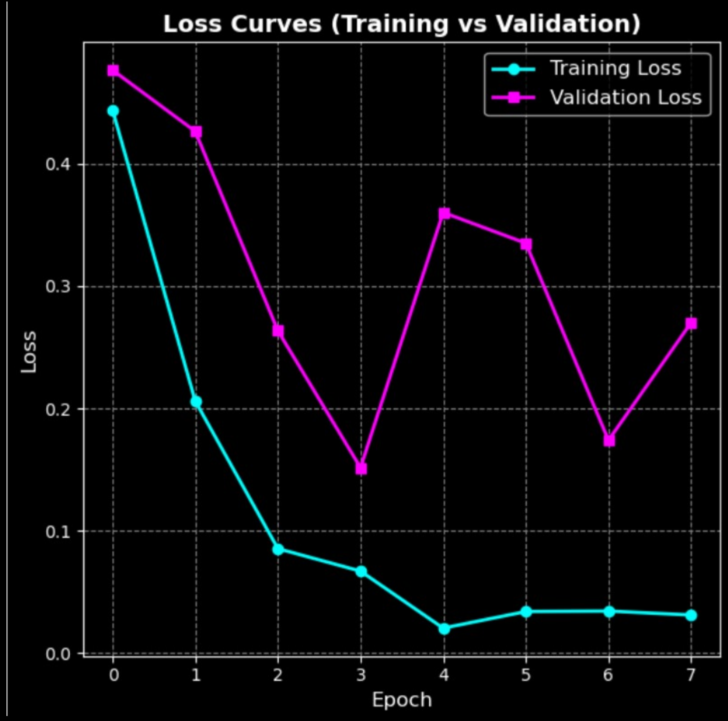

Figure 7: Loss Plot

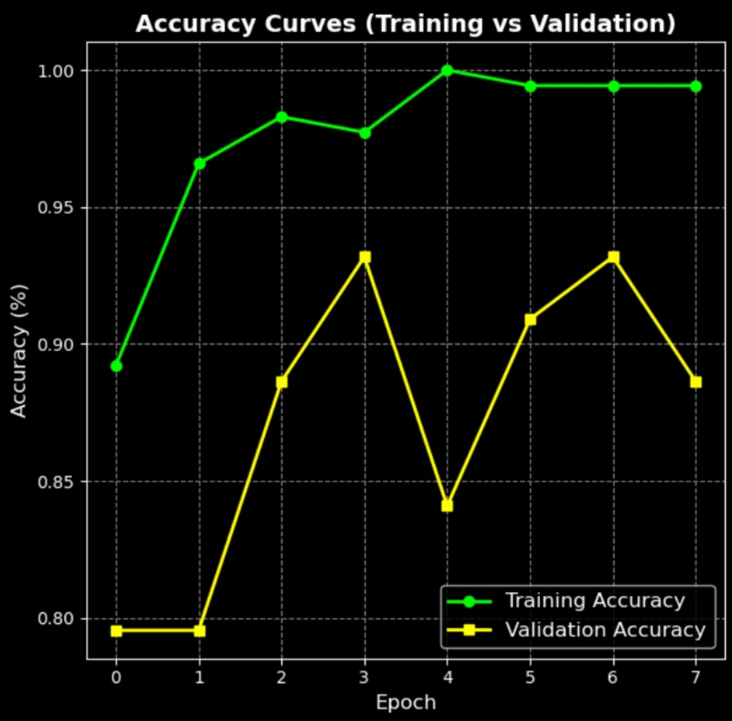

Figure 8: Accuracy Plot

5.4. Age Detection with Masked Faces

Test Metrics:

- AUC Score: 94.18%
- F1-Score: 95.75%
- Precision: 77.04%

Visual Insights:

- **Training and Validation Trends:** Loss and accuracy plots show smooth convergence with no overfitting.
- **Confusion Matrix Visualization:** Displays clear representation of true positives, false positives, and false negatives.
- **Performance Distribution:** Heatmaps provide insight into class-level precision and recall patterns.

5.5. Insights and Future Improvements

Key Takeaways:

- High accuracy and reliability achieved in face mask detection and related tasks.
- Models demonstrated strong generalization across test datasets.

Future Improvements:

- Incorporating larger and more diverse datasets to enhance robustness.
- Exploring ensemble models for further performance improvements.
- Fine-tuning hyperparameters to optimize recall for specific tasks.

6. Conclusion

6.1. Problem Restatement and Objective

With the increasing global concern about respiratory diseases and viral outbreaks, particularly in regions like Pakistan, the need for systems that ensure public health safety has never been more critical. The Unified Face Insight System was developed with the following goals:

- Detect face mask usage and types.
- Identify gender and estimate the age of mask-wearing individuals.
- Provide real-time insights for ensuring compliance with public health guidelines, especially during outbreaks such as COVID-19.

The aim is to enhance public safety by leveraging AI-driven solutions for monitoring health protocols across various environments, from public spaces to workplaces.

6.2. Key Findings and Contributions

The system integrates four advanced AI technologies, each targeting a specific aspect of public health monitoring:

2.1 Face Mask Detection

Technology: Convolutional Neural Networks (CNN)
Application: Detects face mask usage in real-time, a crucial feature for monitoring health protocols during viral outbreaks.

2.2 Mask Type Classification

Technology: ResNet50v2
Application: Classifies different types of masks (cloth, surgical, N95, etc.), ensuring safety standards are met.

2.3 Gender Detection

Technology: PyTorch-based facial recognition
Application: Identifies the gender of individuals even with partial face coverage, helping in demographic analysis.

2.4 Age Detection

Technology: DenseNet121 model
Application: Estimates the age of individuals wearing masks, offering demographic insights that guide health interventions.

These contributions make the system a powerful tool for ensuring public health safety during health crises.

6.3. Real-Life Applicability and Impact

The system's applicability spans various sectors, from public health monitoring to data-driven decision-making:

3.1 Health Safety Monitoring **Application:** Ensures mask compliance in high-risk environments.
Impact: Reduces the spread of diseases during respiratory outbreaks like COVID-19 by enforcing mask-wearing.

3.2 Healthcare Decision Support **Application:** Collects demographic data (age and gender) to provide insights.
Impact: Aids in targeted resource allocation and demographic health interventions.

3.3 Scalability and Global Impact **Application:** Adaptable for worldwide use in public spaces and workplaces.
Impact: Helps countries enforce health regulations globally, especially during viral outbreaks.

3.4 Data-Driven Public Health Strategies **Application:** Provides detailed reports on mask usage, demographics, etc.
Impact: Supports evidence-based decision-making for public health strategies and resource distribution.

6.4. Broader Implications

Beyond real-time monitoring, the system plays a significant role in enhancing public health efforts:

4.1 Improving Compliance Ensures real-time compliance with health protocols, boosting the effectiveness of safety measures.

4.2 Disease Prevention Contribution By continuously monitoring mask usage, the system contributes to preventing the spread of respiratory diseases, especially in high-risk areas.

4.3 Enhanced Surveillance Facilitates large-scale surveillance to ensure that public health protocols are being followed, especially during health crises.

6.5. Future Potential

The system's future includes several possibilities for further enhancing public health safety:

5.1 Integration with Other Health Technologies Future versions can integrate temperature scanners, symptom detection systems, and other health technologies to create a more comprehensive health monitoring system.

5.2 Expansion Beyond Respiratory Diseases While designed for respiratory diseases, the system could be adapted to monitor other health crises, including virus outbreaks and pandemic measures.

This section demonstrates how the Unified Face Insight System can not only address current public health challenges but also contribute to future global health safety initiatives.

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7. References

7.1 GitHub Repositories and Notebooks

1. https://github.com/adityaasawant/Face-mask-detection-and-Age-prediction-with-Email-Authentication/blob/master
2. https://github.com/VatsaPatel9/Masked-Face-Analysis-via-Multi-Task-Deep-Learning
3. https://www.kaggle.com/code/chihjungwang/gender-detection-by-pytorch-acc-91

7.2 Articles and Tutorials

1. https://buffml.com/face-mask-detection-gender-age-prediction/

7.3 Datasets

1. https://www.kaggle.com/datasets/banilkumar20phd7071/masked-face-age-and-gender-identify-artificial-masking
2. https://www.kaggle.com/datasets/trainingdatapro/gender-detection-and-classification-image-dataset/data
3. https://www.kaggle.com/datasets/bahadoreizadkhah/face-mask-types-dataset
4. https://www.kaggle.com/datasets/ashishjangra27/face-mask-12k-images-dataset