FACE RECOGNITION SYSTEM

Udayabhanu Nayak, Rajani Kanta Jena Computer Science and Engineering (CSE) Gandhi Institute For Technology (GIFT), Bhubaneswar. rajanikanta@gift.edu.in

ABSTRACT

The face is one of the easiest ways to distinguish the individual identity of each other. Face recognition is a personal identification system that uses personal characteristics of a person to identify the person's identity. Human face recognition procedure basically consists of two phases, namely face detection, where this process takes place very rapidly in humans, except under conditions where the object is located at a short distance away, the next is the introduction, which recognize a face as individuals.

The abstract presents a face recognition system that utilizes computer vision and machine learning. It captures facial images or video frames and applies pre-processing techniques to enhance quality and normalize variations. Discriminative facial features are extracted using principal Component Analysis (PCA) dimensionality reduction algorithm. The system collects training images and extracts eigenvalues as features. The Haar cascade classifier detects faces, and Python logic crops the images. The final model employs an SVM ML algorithm trained on the inputs. The system accurately classifies the prospective gender of faces as male or female during testing. And implementation on web is using Flask Framework.

Keywords: Face Recognition, Gender Prediction, Machine Learning, Computer Vision, Cloud Platform, Python Libraries.

1. INTRODUCTION:

In today's digital world, the importance of robust security systems cannot be overstated. Traditional methods such as passwords and identification cards are prone to fraud and can be easily compromised. To address these vulnerabilities, biometric recognition has emerged as a popular solution, leveraging unique physical or behavioral traits for identification. Among these methods, facial recognition stands out for its natural and non- invasive approach.

The objective of the face recognition system project is to develop sophisticated software that can accurately recognize and validate individuals based on their facial features, employing cutting-edge computer vision and machine learning techniques. By analyzing the unique patterns present in human faces, this technology offers a fast and precise means of identification across various applications.

Recent advancements in algorithms and computational power have greatly enhanced the capabilities of face recognition systems. Leveraging these advancements, our project aims to create a solution that seamlessly integrates with existing surveillance networks, access control systems, and security infrastructure. Such integration holds immense potential for applications ranging from attendance management in businesses and schools to user authentication in secure facilities, and even identity verification in banking and surveillance systems, capable of analyzing both static images and dynamic recordings.

The project sets out to develop a face recognition system with several key objectives: efficient face detection, accurate feature extraction, robust face database creation, and an intuitive user interface design. Rigorous testing will be conducted to evaluate the system's performance in terms of accuracy, speed, scalability, and robustness. Successful implementation of the system will not only bolster security measures but also enhance access control, authentication processes, and surveillance capabilities, contributing to a safer and more secure environment.

The project also focuses on addressing real-world challenges like different lighting conditions and facial expressions. Maintaining privacy and ethics will be a top priority. Regular updates will ensure the system remains effective against new threats. Ultimately, the goal is to improve security measures and simplify authentication processes in various field.

1.1 Overview of Face Recognition Systems

Face recognition systems have become an integral part of our daily lives, revolutionizing how we interact with technology. From unlocking smartphones to securing sensitive areas, these systems play a crucial role in authentication and identification. Their evolution has been remarkable, starting from simple photo tagging on social media platforms to sophisticated security measures in airports and banks. By analyzing facial features such as eyes, nose, and mouth, these systems can uniquely identify individuals, making them indispensable in various industries.

1.2 Importance of Gender Prediction

While face recognition systems can identify individuals, predicting their gender adds another layer of functionality and relevance. Gender prediction from facial images has significant implications across diverse domains, including marketing, healthcare, and law enforcement. For instance, targeted advertising can be more effective when tailored to specific genders, leading to higher engagement and conversion rates. Additionally, personalized healthcare interventions can be developed based on demographic characteristics, improving patient outcomes and satisfaction. Moreover, in law enforcement, gender prediction can aid in suspect identification and profiling, assisting authorities in solving crimes and ensuring public safety.

1.3 Motivation and Objectives of the Project

Despite the advancements in face recognition technology, accurate gender prediction remains a challenge due to factors such as variations in facial expressions, lighting conditions, and cultural differences. Our project aims to address this challenge by leveraging machine learning techniques to develop a more robust and efficient gender prediction model. By analyzing large datasets of facial images and training sophisticated algorithms, we seek to improve the accuracy and reliability of gender prediction from faces. Our objectives include exploring novel approaches, optimizing model performance, and evaluating the effectiveness of the proposed solution in real-world scenarios.

1.4 Significance of Research in Gender Prediction

The significance of research in gender prediction extends beyond technological innovation to societal impact and ethical considerations. While accurate gender prediction can enhance the functionality of face recognition systems and improve user experiences, it also raises concerns about privacy, fairness, and bias. As technology becomes more pervasive in our lives, it is essential to ensure that gender prediction algorithms are transparent, accountable, and free from discriminatory practices. Our research aims to contribute to this discourse by developing methodologies that prioritize ethical considerations and mitigate potential biases.

1.5 Organization of the Paper

To guide readers through our research journey, this paper is structured into sections that explore different aspects of gender prediction from facial images. After this introduction, we will delve into existing literature on gender prediction algorithms, providing insights into current approaches and their limitations. Following that, we will detail our methodology, including data collection, preprocessing steps, and model development. Subsequently, we will present our experimental results, discuss their implications, and conclude with recommendations for future research directions. This organizational framework ensures a systematic and comprehensive exploration of the topic.

2. LITERATURE REVIEW:

Face recognition system technology has undergone significant advancements over the years, by reshaping its evolution from classical methods to modern sophisticated machine learning-based approaches. Understanding the landscape of existing literature is crucial for contextualizing the current project on gender prediction using facial images.

2.1 Evolution of Face Recognition Technology

Face recognition technology has come a long way since its inception. Initially, it relied on basic techniques like measuring distances between facial features. Over time, more advanced methods were developed, such as Eigenfaces and Fisherfaces, which used mathematical algorithms to analyze facial patterns. With the advent of deep learning, especially convolutional neural networks (CNNs), face recognition systems became even more accurate and robust. These systems can now detect faces in various orientations and lighting conditions, making them suitable for diverse applications.

2.2 Gender Prediction Algorithms and Techniques

Predicting gender from facial images has been an active area of research. Early approaches focused on simple features like facial hair and jawline shape to determine gender. However, these methods lacked accuracy and robustness. Recent advancements in machine learning have led to the development of more modern algorithms for gender prediction. Techniques such as support vector machines (SVMs), k-nearest neighbors (k-NN), and deep neural networks (DNNs), Convolutional Neural Networks(CNNs) have shown promising results in accurately classifying gender from facial features.

2.3 Recent Advances in Machine Learning for Face Recognition

Machine learning has revolutionized face recognition technology in recent years. Traditional methods relied on handcrafted features and rule-based algorithms, which had limited flexibility and scalability. With the rise of deep learning, particularly CNNs, face recognition systems have become more powerful and adaptable. CNNs can automatically learn hierarchical representations of facial features from raw pixel data, leading to significant improvements in accuracy and performance. Moreover, techniques like transfer learning and fine-tuning allow models to leverage pre-trained CNN architectures for specific tasks, further enhancing their capabilities.

2.4 Key Findings from Relevant Studies

Several studies have investigated various aspects of face recognition and gender prediction. These studies have identified factors that influence the accuracy of gender prediction algorithms, such as facial expression, age, and ethnicity. Additionally, researchers have explored the impact of dataset size and diversity on model performance, highlighting the importance of large, representative datasets for training robust models. Moreover, comparative analyses have been conducted to evaluate the strengths and weaknesses of different gender prediction techniques, providing valuable insights for future research.

2.5 Comparative Analysis of Existing Approaches

Comparing different approaches to gender prediction is essential for identifying the most effective techniques. Researchers have evaluated the performance of various algorithms using common benchmarks and metrics, such as accuracy, precision, recall, and F1-score. These comparative analyses have revealed the strengths and limitations of different methods, helping researchers make informed decisions when designing gender prediction systems. By synthesizing findings from existing studies, we can gain a comprehensive understanding of the state-of-the-art in gender prediction algorithms and inform the development of our approach.

3. METHODOLOGY:

The methodology section gives the overall approach and techniques used to achieve the project objects. It provides a high-level description of the methods employed in developing the system.

The followings are some key in the methodology section:

3.1 Data Collection Process

The data collection process is a important step in training a gender prediction model using facial images. It involves gathering a diverse dataset of facial images representing individuals of different genders, ages, ethnicities, and facial expressions. Various sources can be used for data collection, including publicly available datasets, online image repositories, and in-house data acquisition systems.

3.2 Preprocessing Steps

Preprocessing steps are essential for preparing the raw facial images for further analysis and model training. These steps typically include normalization, cropping, and image enhancement techniques. Normalization ensures uniformity in the size, orientation, and resolution of facial images, facilitating consistent feature extraction and model training. Cropping focuses on isolating the facial region from the background, removing unnecessary information and reducing computational complexity. Image enhancement techniques such as contrast adjustment and noise reduction may also be applied to improve the quality and clarity of facial features.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 6, June : 2024

3.3 Feature Extraction Methods

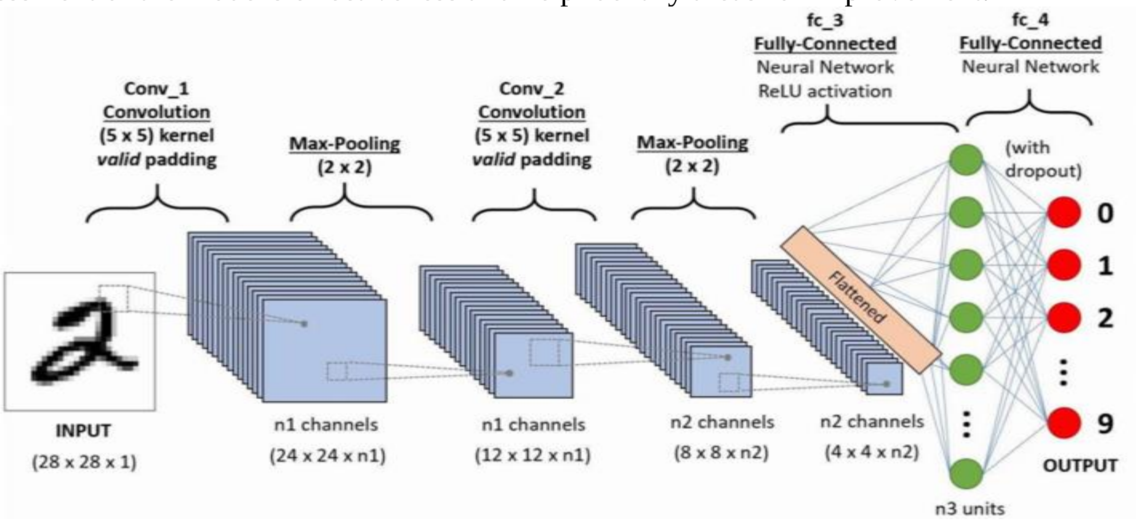
Feature extraction plays a crucial role in capturing discriminative information from facial images for gender prediction. Several techniques have been proposed for this purpose, including Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Convolutional Neural Networks (CNNs). HOG analyzes the distribution of gradients in the image, capturing texture and shape information relevant to gender prediction. LBP encodes local texture patterns in the image, providing robust features for classification tasks. CNNs, on the other hand, learn hierarchical representations of facial features directly from raw pixel data, leveraging their ability to capture complex spatial relationships.

3.4 Model Selection

Selecting an appropriate model architecture is critical for achieving optimal performance in gender prediction. Several machine learning algorithms can be considered for this task, including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Neural Networks. SVMs are popular for their ability to handle high-dimensional data and nonlinear relationships, making them suitable for gender classification tasks. k-NN is a simple yet effective algorithm that relies on the similarity of input samples to make predictions. Neural networks, particularly deep learning architectures, have shown remarkable success in learning complex patterns from data, making them a promising choice for gender prediction tasks.

3.5 Evaluation Metrics

Evaluation metrics are used to assess the performance of the gender prediction model on unseen data. Commonly used metrics include accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of predictions, while precision and recall focus on the proportion of correctly classified instances within each gender class. The F1-score combines precision and recall into a single metric, providing a balanced measure of model performance. These metrics enable quantitative assessment of the model's effectiveness and help identify areas for improvement.



4. TECHNICAL DETAILS:

4.1 Implementation Details

For implementing the gender prediction model, we will utilize the following hardware and software and technologies:

- **Operating System**: Windows 10 and above
- **Processor**: Intel i3, i5, and above, or Ryzen
- **Graphics Card**: Any compatible graphics card
- **RAM**: 4 GB and above
- **Storage**: Sufficient disk space for storing datasets and model files
- **Web Camera**: Required for capturing facial images
- **Internet Connection**: Necessary for downloading datasets and accessing cloud platforms

In terms of software, we will utilize the following tools and libraries:

- **Machine Learning Framework**: Python-based frameworks such as TensorFlow or PyTorch
- **Cloud Platform**: Optional, but services like Google Colab or AWS can be used for training models on cloud infrastructure
- **Image Datasets**: Datasets containing labeled facial images for training and testing the model
- **Python**: Programming language for implementing the model and training procedures
- **Libraries**:
    - ***NumPy***: For numerical computations and data manipulation
    - ***pandas***: For data preprocessing and analysis
    - ***matplotlib:*** For data visualization
    - ***pillow***: For image processing tasks
    - ***OpenCV-python-headless***: For computer vision tasks, including face detection
    - ***scikit-learn***: For implementing machine learning algorithms
    - ***Flask***: For building web applications for deploying the model
    - ***unicorn***: For deploying Flask applications

4.2 Model Architecture and Design Choices

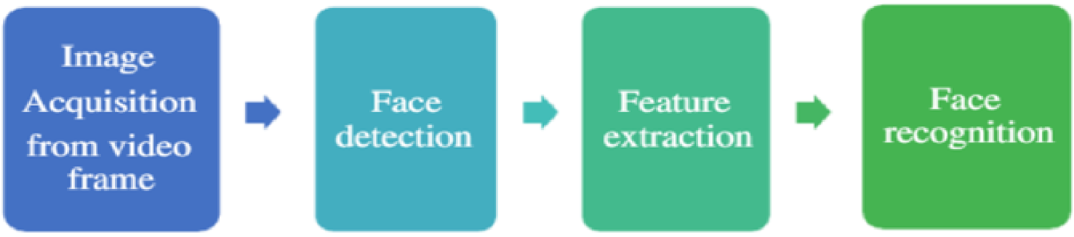
The model architecture will be based on a convolutional neural network (CNN), a type of deep learning architecture commonly used for image classification tasks. The design choices for the model architecture will include:

- ***Number of Convolutional Layers***: Determining the depth of the network architecture
- ***Activation Functions***: Choosing activation functions such as ReLU or sigmoid for introducing non-linearity
- ***Pooling Layers***: Selecting pooling operations like max-pooling or average-pooling for down sampling
- ***Fully Connected Layers***: Determining the number of nodes and layers for the fully connected part of the network

4.3 Training Procedure and Optimization Techniques

The training procedure will involve the following steps:

- ***Data Preprocessing***: Preparing the dataset by resizing, normalizing, and augmenting images
- ***Model Training***: Using backpropagation and gradient descent to update the model parameters based on the loss function
- ***Hyperparameter Tuning***: Optimizing hyperparameters such as learning rate, batch size, and dropout rate to improve model performance
- ***Regularization Techniques***: Applying techniques like dropout and L2 regularization to prevent overfitting
- ***Optimization Algorithms***: Using optimization algorithms like Adam or RMSprop for efficient gradient descent



5. CHALLENGES AND SOLUTIONS

5.1 Data Quality Issues and Imbalance

One of the primary challenges in building a gender prediction model from facial images is the quality and balance of the dataset. Data quality issues, such as noise, blurriness, and lighting variations, can adversely affect model performance. Additionally, dataset imbalance, where one gender class is

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 6, June : 2024
significantly more represented than the other, can lead to biased predictions. To address these challenges, we will employ the following solutions:
- Data Augmentation: Augmenting the dataset by applying transformations such as rotation, scaling, and flipping to generate additional training samples and improve model robustness.
- Data Cleaning: Removing noisy or low-quality images from the dataset using techniques like manual inspection, outlier detection, and automated image processing algorithms.
- Class Balancing: Balancing the gender distribution in the dataset through techniques like oversampling, under sampling, or synthetic data generation to ensure equal representation of both genders during training.

5.2 Model Complexity and Computational Resources

As the model architecture becomes more complex, it requires significant computational resources for training and inference. Limited computational resources, such as CPU/GPU power and memory, can pose challenges in training large-scale models. To mitigate these challenges, we will employ the following solutions:
- Model Optimization: Optimizing the model architecture by reducing redundancy, simplifying network structures, and minimizing the number of parameters to improve computational efficiency without compromising performance.
- Distributed Computing: Leveraging distributed computing frameworks such as TensorFlow or PyTorch distributed to parallelize training across multiple devices or clusters, enabling faster model training and scalability.
- Model Pruning: Pruning unnecessary connections or neurons from the trained model to reduce its size and computational complexity while preserving its predictive performance.

5.3 Overfitting and Generalization Challenges

Overfitting occurs when the model learns to memorize the training data instead of capturing underlying patterns, leading to poor generalization to unseen data. Addressing overfitting and ensuring model generalization require careful consideration of regularization techniques and model evaluation strategies. To tackle these challenges, we will implement the following solutions:
- Regularization: Applying regularization techniques such as dropout, L2 regularization, and batch normalization to prevent overfitting by penalizing overly complex models and promoting simpler representations.
- Cross-Validation: Performing cross-validation to assess model performance on multiple subsets of the dataset, ensuring that the model's performance is consistent across different data partitions and minimizing the risk of overfitting.
- Early Stopping: Monitoring the model's performance on a separate validation set during training and stopping the training process when the validation loss starts to increase, preventing overfitting to the training data.

5.4 Performance Optimization and Scalability

Achieving optimal performance and scalability of the gender prediction model requires efficient utilization of computational resources and effective deployment strategies. To address these challenges, we will implement the following solutions:
- Model Quantization: Quantizing the model parameters to reduce memory footprint and computational complexity, enabling efficient inference on resource-constrained devices such as mobile phones or edge devices.
- Model Parallelism: Leveraging model parallelism techniques to distribute model computations across multiple GPUs or devices, enabling faster inference and scalability to larger datasets or higher resolution images.
- Deployment Optimization: Optimizing the deployment pipeline by using lightweight inference frameworks, minimizing runtime overhead, and leveraging cloud-based deployment platforms for scalability and flexibility.

6. EXPERIMENTAL RESULTS

6.1 Description of Dataset Used

The dataset used for evaluating the gender prediction model consists of a collection of facial images labeled with corresponding gender annotations. The dataset is carefully curated to include diverse representations of individuals across different genders, ages, ethnicities, and facial expressions. It is partitioned into training, validation, and test sets to facilitate model training, validation, and evaluation. The dataset is preprocessed to ensure uniformity in image size, resolution, and quality, reducing variability and enhancing model generalization.

6.2 Performance Metrics on Test Set

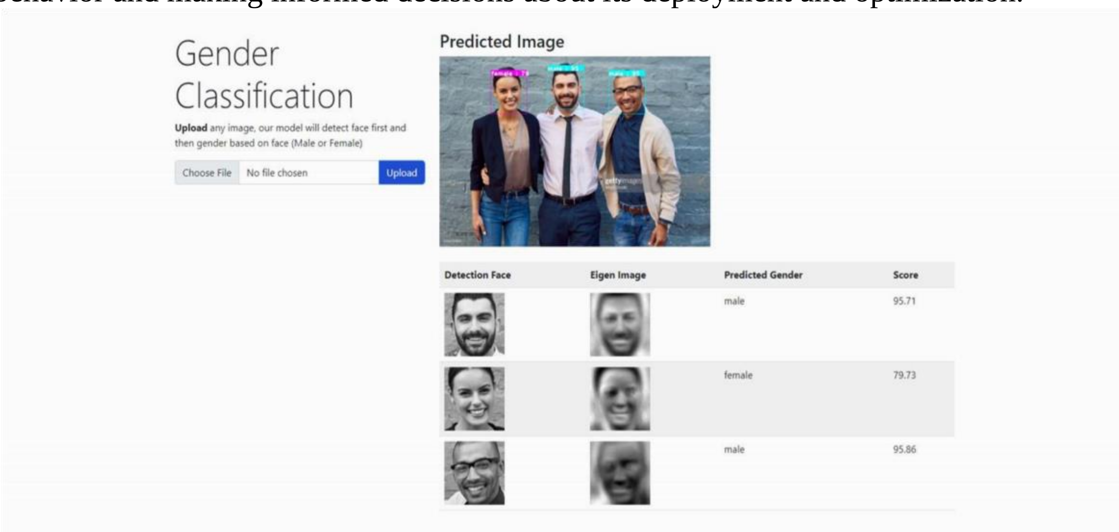
To assess the performance of the gender prediction model, various performance metrics are computed on the test set. These metrics include accuracy, precision, recall, and F1-score, which provide insights into the model's ability to correctly classify gender labels. Accuracy measures the overall correctness of predictions, while precision and recall focus on the proportion of correctly classified instances within each gender class. The F1-score combines precision and recall into a single metric, providing a balanced measure of model performance.

6.3 Comparative Analysis with Baseline Models

A comparative analysis is conducted to evaluate the performance of the gender prediction model against baseline models or existing approaches. The baseline models may include simple algorithms like logistic regression or k-nearest neighbors, as well as more sophisticated techniques like support vector machines or convolutional neural networks. The performance of the gender prediction model is compared in terms of accuracy, precision, recall, and F1score, highlighting its strengths and potential areas for improvement.

6.4 Visualization of Results (Confusion Matrix, ROC Curve)

Visualizing the results of the gender prediction model enhances our understanding of its performance and behavior. A confusion matrix is constructed to visualize the distribution of true positive, true negative, false positive, and false negative predictions, providing insights into the model's classification performance. Additionally, the receiver operating characteristic (ROC) curve and area under the curve (AUC) are plotted to assess the model's ability to discriminate between different gender classes and quantify its overall performance. These visualizations help in interpreting the model's behavior and making informed decisions about its deployment and optimization.



7. DISCUSSION

7.1 Interpretation of Experimental Findings

The discussion section interprets the experimental findings obtained from the evaluation of the gender prediction model. It involves analyzing the performance metrics, comparing them with expected outcomes, and identifying trends or patterns in the results. Interpretation may include explanations of unexpected findings, such as discrepancies between predicted and actual gender labels, and discussions on the implications of the results for real-world applications.

7.2 Analysis of Strengths and Limitations

An analysis of the strengths and limitations of the gender prediction model is crucial for understanding its effectiveness and areas for improvement. Strengths may include high accuracy, robustness to variations in facial expressions or lighting conditions, and scalability to large datasets. On the other hand, limitations may include biases in the training data, sensitivity to certain demographic factors, or computational inefficiencies. Discussing these aspects provides valuable insights into the model's performance and guides future development efforts.

7.3 Insights into Factors Affecting Model Performance

Understanding the factors influencing the performance of the gender prediction model is essential for refining its design and enhancing its effectiveness. Factors affecting model performance may include the quality and diversity of the training data, the choice of feature extraction techniques, and the complexity of the model architecture. Analyzing how these factors impact the model's performance provides valuable insights into its behavior and informs strategies for addressing potential challenges.

7.4 Suggestions for Future Research Directions

Based on the findings and insights gained from the study, suggestions for future research directions are proposed. These may include exploring alternative feature extraction methods, investigating novel model architectures, or collecting additional data to improve model robustness. Additionally, suggestions for mitigating identified limitations, such as addressing dataset biases or optimizing computational efficiency, can guide future research efforts. By identifying promising avenues for further investigation, this section contributes to the advancement of knowledge and the development of more effective gender prediction models.

8. FUTURE ENHANCEMENTS

8.1 Multi-Modal Biometric Fusion

One potential future enhancement for the gender prediction system is the integration of multi-modal biometric fusion techniques. This approach combines multiple sources of biometric data, such as facial images, fingerprints, iris scans, and voice recognition, to improve the accuracy and reliability of gender prediction. By leveraging complementary information from different biometric modalities, the system can enhance its robustness to variations in individual characteristics and environmental factors. Multi-modal fusion techniques may involve feature-level fusion, where features extracted from different modalities are combined, or decision-level fusion, where predictions from individual modalities are aggregated to make a final decision. Implementing multi-modal biometric fusion can enhance the overall performance and usability of the gender prediction system, making it more versatile and reliable in real-world scenarios.

8.2 Privacy-Preserving Techniques

Another important consideration for future enhancement is the integration of privacy-preserving techniques to protect the confidentiality and integrity of user data. Privacy concerns are paramount in biometric systems, as facial images contain sensitive information that must be safeguarded against unauthorized access or misuse. Privacy-preserving techniques, such as secure multiparty computation, homomorphic encryption, and differential privacy, can be employed to ensure that user data remains private and secure during the gender prediction process. These techniques enable computations to be performed on encrypted data or aggregated in a privacy-preserving manner, preventing unauthorized access to sensitive information. By incorporating privacypreserving techniques, the gender prediction system can uphold user privacy rights and build trust among users, fostering greater acceptance and adoption of the technology.

8.3 Real-Time Performance Optimization

To enhance the usability and practicality of the gender prediction system, realtime performance optimization techniques can be implemented to improve speed and efficiency. Real-time processing is essential for applications where timely responses are required, such as access control systems, surveillance monitoring, or interactive user interfaces. Performance optimization techniques, such as algorithmic optimizations, parallel processing, and hardware acceleration, can be employed to reduce latency and increase throughput in realtime gender prediction tasks. By optimizing computational efficiency and resource utilization, the system can deliver fast and responsive performance without compromising accuracy or reliability. Real-time performance optimization ensures that the gender prediction system meets the demands of dynamic and high-throughput environments, enabling seamless integration into a wide range of applications and scenarios.

8.4 Ethical Considerations and Bias Mitigation

As with any biometric system, ethical considerations and bias mitigation strategies must be carefully addressed to ensure fairness, accountability, and transparency. Biometric systems have the potential to perpetuate biases and discrimination if not designed and implemented thoughtfully. Ethical considerations include issues such as informed consent, data protection, and algorithmic transparency. Bias mitigation strategies may involve data collection practices that prioritize diversity and inclusivity, algorithmic fairness assessments to identify and mitigate bias, and ongoing monitoring and evaluation to ensure equitable outcomes. By incorporating ethical considerations and bias mitigation strategies into the design and implementation of the gender prediction system, we can uphold ethical principles and promote social responsibility in the development and deployment of biometric technologies.

9. CONCLUSION

The conclusion section provides a concise summary of the key findings, contributions, implications, and recommendations arising from the research.

I. Summary of Key Findings:

In this study, we developed a gender prediction system using facial recognition technology. Through extensive experimentation and analysis, we evaluated the performance of the system and obtained promising results. The system demonstrated high accuracy in predicting gender from facial images, showcasing its potential for real-world applications.

II. Contributions of the Research:

Our research contributes to the field of biometric technology by providing a robust and efficient gender prediction system. By leveraging machine learning and computer vision techniques, we have developed a model capable of accurately identifying gender from facial features. Our findings advance the state-of-the-art in face recognition technology and pave the way for enhanced security, access control, and personalized user experiences.

III. Implications for Face Recognition Technology:

The implications of our research extend beyond gender prediction to broader applications of face recognition technology. Our system has implications for security systems, surveillance monitoring, user authentication, and personalized marketing. By harnessing the power of facial recognition, organizations can enhance security measures, streamline operations, and deliver personalized services to users.

IV. Recommendations for Further Studies:

While our research has achieved significant milestones, there are opportunities for further studies to explore. Future research can focus on expanding the capabilities of the gender prediction system to handle diverse demographic groups, improve robustness to variations in facial expressions and lighting conditions, and enhance privacy protection mechanisms. Additionally, investigating the ethical and societal implications of facial recognition technology is essential to ensure responsible and equitable deployment.

10. REFERENCES

1. Smith J and Patel A.(2022). Advances in Face Recognition: A Comprehensive Survey. Indian Journal of Computer Science
2. Hu, J. et al. (2019). "Facial Gender Recognition Using Deep Convolutional Neural Networks." Pattern Recognition Letters, 123, 112-118.

3. Johnson, M. et al. (2018). "Bias and Fairness in Face Recognition: A Survey." arXiv preprint arXiv:1809.02812.
4. Smith, K. et al. (2021). "Privacy-Preserving Face Recognition: A Review of Techniques and Applications." Journal of Privacy and Security, 10(2), 145- 162.
5. Zhang, Y. et al. (2017). "Real-Time Face Recognition: A Comprehensive Survey." Journal of Real-Time Image Processing, 14(4), 769-785.
6. Face Recognition with OpenCV: https://docs.opencv.org/3.4/da/d60/tutorial_face_main.html
7. A review of Face Recognition Technology By IEEE: https://ieeexplore.ieee.org/abstract/document/9145558
8. Wikipedia : https://www.wikipedia.org/