



Optimized dataset creation for real time facial recognition

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Abstract

This study investigates optimizing dataset creation for real time facial recognition attendance tracking. It explores the impact of grayscale conversion intensity values on preprocessing time and accuracy. Data from six staff members, with 80 images each, were collected under controlled conditions. Grayscale conversion was applied with intensity values of 255, 127, and 95, followed by face detection and feature extraction. SVM and KNN classification algorithms were assessed across the three datasets, with the 127 intensity value showing the most promising balance between time and accuracy. SVM achieved accuracies of 96.88%, 94.79%, and 94.79% with preprocessing times of 0.036, 0.02, and 0.017 seconds for intensity values 255, 127, and 95, respectively. KNN accuracies were 88.54%, 87.50%, and 81.25%, with preprocessing times of 0.036, 0.02, and 0.017 seconds for intensity values 255, 127, and 95, respectively. Lower intensity values like 127 and 95 demonstrated efficiency in balancing accuracy and preprocessing time, aiding in efficient attendance tracking. Grayscale conversion value of 127 offers a compelling balance between accuracy and efficiency, recommended for optimized facial recognition datasets in real-time attendance tracking applications. The study's significance was highlighted through comparisons with existing literature, positioning it as a pioneering effort in dataset optimization for real-world applications.

Keywords: Grayscale Conversion, Preprocessing time, Real time Attendance, Support Vector Machine (SVM), K-Nearest Neighbor (KNN)

Introduction

Background to the study

Facial recognition technology has revolutionized various industries, offering unprecedented capabilities in identity verification and security. By analyzing unique facial features, such as the arrangement of eyes, nose, and mouth, facial recognition systems create digital representations known as faceprints. These faceprints are then compared against databases of known faces to determine matches. In educational institutions like the Centre for Information and Telecommunication Engineering (CITE), the integration of facial recognition technology for attendance tracking and security purposes is gaining traction. Traditional attendance tracking methods are prone to errors and time-consuming, prompting the adoption of facial recognition systems for real-time identification of students as they enter classrooms or designated areas. The effectiveness of facial recognition systems in educational settings depends on various factors, including the quality of datasets used for training and the performance of underlying algorithms. Real-time processing capabilities are crucial for ensuring timely identification and response in dynamic environments like classrooms. By investigating different grayscale conversion intensity values and evaluating their impact on preprocessing time and system performance, this research aims to optimize facial recognition dataset creation for an optimal approach to enhance the reliability and efficiency of real time facial recognition for attendance tracking.

Literature review

1. Dataset Creation and Preparation for Facial Recognition Attendance Tracking

Dataset creation and preparation for facial recognition attendance tracking involves the meticulous collection, labeling, and preprocessing of facial images to facilitate

accurate identification and verification of individuals. This process entails gathering a diverse range of facial images representing various demographics, lighting conditions, and facial expressions. Additionally, dataset preparation includes tasks such as normalization, alignment, and feature extraction to enhance the quality and consistency of the facial data. By carefully curating and preparing the dataset, researchers and practitioners can ensure the reliability and effectiveness of facial recognition systems for attendance tracking applications.

Facial recognition algorithms incorporate classification techniques to match extracted features with pre-existing templates or identities stored in a database. Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and decision trees are among the classification models commonly used in facial recognition systems. These models compare extracted features with known identities to determine the most likely match, enabling accurate identification of individuals. In the context of attendance tracking, facial recognition algorithms must be robust to variations in lighting, pose, facial expression, and occlusions.

2. Related works on Facial Recognition for Attendance Tracking

Trushna *et al.*, (2021) in ^[1] purposed the implementation of a facial recognition-based attendance system using the Local Binary Patterns Histograms (LBPH) algorithm. The literature underscores the system's ability to simplify attendance tracking by eliminating manual methods such as calling out student names or checking identification cards. Through LBPH in the OpenCV framework, the system effectively trains and recognizes students' faces. Python automation further streamlines program execution, computer vision, GUI management, and database

maintenance for attendance records. The study highlights the system's efficacy in mitigating fraudulent attendance practices and reducing manual errors. Overall, the smart attendance system, based on facial recognition techniques, proves to be time-saving and efficient, with potential applications in various educational and organizational settings. This literature contributes to the understanding of how traditional facial recognition models, particularly LBPH, can revolutionize attendance management practices and enhance operational efficiency in educational institutions.

Murthy *et al.*, (2023) in ^[2] emphasized the significance of face recognition systems in various sectors, particularly for attendance management in educational institutions. It outlines the advantages of face recognition despite its lower accuracy compared to other biometric methods. The proposed system aims to automate attendance marking through four phases: database creation, face detection, recognition, and attendance updating. Utilizing Haar-Cascade classifier and machine learning techniques, the system detects and recognizes students' faces from live streaming video, eliminating manual attendance marking. Additionally, it enhances school security by monitoring student movements. Overall, this system promised to revolutionize attendance management in schools/colleges by offering a faster, more accurate, and efficient solution.

The implementation of the deep learning system Mobile-FaceNet has significantly improved the process of taking attendance. With an accuracy of up to 85% when faces are labeled and 90% when they are recognized, this system offers a reliable alternative to manual attendance tracking. By reducing the time required for attendance taking and replacing RFID card systems, the institution can minimize the risk of card loss impacting attendance records and decrease the likelihood of fraudulent attendance. Consequently, effective attendance control contributes to preventing unauthorized admission, thereby benefiting the institution as a whole (Pandey *et al.*, 2023) ^[3].

Akash *et al.*, (2021) in ^[4] introduced an automated student attendance system leveraging face recognition technology. It emphasizes the importance of face detection and segmentation using the Histogram of Oriented Gradient (HOG) algorithm. The system undergoes preprocessing stages including image scaling, noise removal, and contrast enhancement to optimize recognition accuracy. Implemented in Python, it efficiently accesses a database, conducts necessary conversions for recognition, and updates attendance records upon successful matches.

Gupta *et al.*, (2023) in ^[5] proposed system effectively achieves its objective of high precision and reduced computational complexity, offering cost-efficiency and minimizing manual labor. Employing Gabor filters significantly enhances accuracy. Utilizing three face recognition algorithms—K-nearest neighbor, convolutional neural networks (CNNs), and support vector machine (SVM)—the KNN algorithm stands out with an impressive accuracy of 99.27%. While CNNs demonstrate lower computational complexity, SVM lags behind in efficiency. This comprehensive approach showcases the potential of combining multiple algorithms to optimize performance in face recognition systems. However, further exploration could focus on improving SVM efficiency to ensure a more balanced performance across all algorithms.

Facial Expression Recognition (FER) has garnered significant attention in image processing due to its vital role. This paper introduces an automatic system capable of recognizing all eight basic facial expressions, a notable advancement compared to prior systems that typically focused on recognizing only a subset of expressions. Utilizing the Viola-Jones algorithm for face detection and Histogram of Oriented Gradients (HOG) for feature extraction, the method employs Principal Component Analysis (PCA) to reduce feature dimensionality. Three classifiers—Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Multilayer Perceptron Neural Network (MLPNN)—are employed for expression classification. Experimental validation on the Extended Cohn-Kanade (CK+) dataset demonstrates promising results, with the SVM classifier achieving the highest recognition rate of 93.53%, outperforming MLPNN (82.97%) and KNN (79.97%). These findings underscore the effectiveness of the proposed method, particularly when leveraging SVM for expression classification (Hivi *et al.*, 2019) ^[6].

The gaps in the related works includes the lack of focus in the optimization of datasets for real-time facial detection, particularly in terms of reducing preprocessing time while maintaining accuracy, limited exploration of the impact of different intensity values on preprocessing time and accuracy as existing researches often employs default intensity values without considering potential variations that could optimize the dataset for real-time detection, also, there is a gap in understanding how different dataset optimization strategies can affect preprocessing time and overall system performance on resource-constrained devices. This research aims to balance preprocessing time and accuracy to achieve reliable and efficient facial recognition outcomes.

Methodology

1. Overview of the Proposed Methodology

In the process of constructing the dataset for facial recognition, meticulous steps are taken to ensure the collection of high-quality and diverse data. The initial phase involves data acquisition, where images capturing facial data are obtained from six participants representing various departments at CITE. A total of 80 images are captured per participant using a designated camera, capturing a range of facial expressions including neutral, smiling, surprised, angry, sad, eyes closed, various head poses, pensive, happy, and concentrated expressions. This comprehensive dataset is essential for training robust facial recognition algorithms capable of accurately identifying individuals in real-world scenarios. Following data acquisition, the images are meticulously labeled with the participants' identities, ensuring each image is accurately associated with the correct individual.

Data collection and labeling are critical components of dataset construction, requiring meticulous implementation to ensure accuracy and reliability. The process involves acquiring a diverse set of facial images from CITE staff, capturing various facial expressions and poses to create a comprehensive dataset. Ethical considerations regarding consent and privacy are prioritized throughout the data collection process, with participants providing explicit permission for image capture and usage. Each captured image is manually labeled with the respective individual's identity, facilitating subsequent training and evaluation of

the facial recognition system. The meticulous labeling process ensures the dataset's integrity and enables precise identification of individuals during algorithm training and testing. Additionally, metadata such as gender, age, and other relevant attributes are recorded to enrich the dataset and enable more detailed analysis. Overall, the systematic approach to data collection and labeling ensures the dataset's quality and reliability, laying a solid foundation for the subsequent phases of the research.

Following data collection and labeling, the dataset undergoes a series of preprocessing techniques to enhance its quality and standardization. These techniques involve resizing the images to a standardized resolution, cropping to focus on facial regions, and converting to grayscale to simplify feature extraction. Additionally, noise reduction techniques are applied to improve image clarity and remove background interference. These preprocessing steps are crucial for standardizing the dataset and removing irrelevant information that could hinder accurate facial recognition.

Once the dataset is preprocessed, face detection algorithms using Haar Cascade Classifier are applied to identify and locate faces within the images. These algorithms utilize pattern recognition techniques to detect facial features such as eyes, nose, and mouth, enabling accurate localization of

faces within the images. Face detection is a fundamental step in facial recognition systems, as it enables the system to isolate and analyze facial features for subsequent processing.

After face detection, feature extraction methods are employed to extract relevant facial features for further analysis. These methods aim to capture distinctive characteristics of the face, such as shape, texture, and spatial arrangements of facial landmarks. Common feature extraction techniques like Local Binary Pattern Histograms (LBPH) are used to extract meaningful features from the facial images, the dataset becomes more informative and suitable for training robust facial recognition models.

Subsequently, the preprocessed and feature-extracted dataset is partitioned into training and testing sets to facilitate the development and evaluation of facial recognition algorithms. The training set is used to train the classification models, such as Support Vector Machine (SVM) and K-Nearest Neighbour (KNN), while the testing set is used to assess the performance of the trained models on unseen data. Careful consideration is given to the distribution of data in each set to ensure a representative sample of the overall dataset. This partitioning enables the evaluation of the models' performance in real-world scenarios and facilitates the identification of potential areas for improvement.

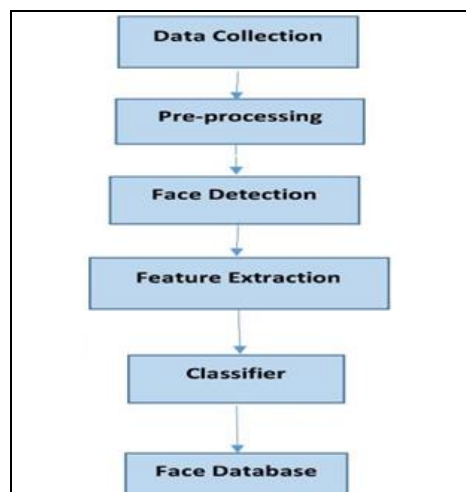


Fig 1: Block diagram of the proposed methodology

2. Software Tools for Implementation

The software tools used for creating a facial recognition system include Python for its versatility and rich libraries, OpenCV for image processing like face detection, PIL (Pillow) for image augmentation, Matplotlib for visualization, and Scikit-learn for implementing classification algorithms such as SVM and KNN. These tools enable efficient data handling, image manipulation, feature extraction, model training, and evaluation for building an accurate facial recognition system.

3. Dataset Evaluation and Validation

The performance Datasets would be assessed using performance Metrics like accuracy, precision, recall, F1 score and confusion matrix. The Dataset would be validated by comparing the performance of different facial recognition systems in existing literatures. By evaluating

existing research and benchmarking studies, we aim to establish a solid foundation for our own performance assessment, enabling us to make informed decisions and recommendations for the deployment of facial recognition technology.

Results and discussion

1. Results of Data Collection and Grayscale Conversion Process

The data collection process by seeking consent from six staff members at CITE, ensuring adherence to ethical guidelines. Utilizing a digital camera, we meticulously captured a series of 80 images per participant. Each image session encompassed various head poses and facial expressions. The grayscale conversion process resulted in three distinct datasets, each representing grayscale images with varying intensity values; 255, 127 and 95.

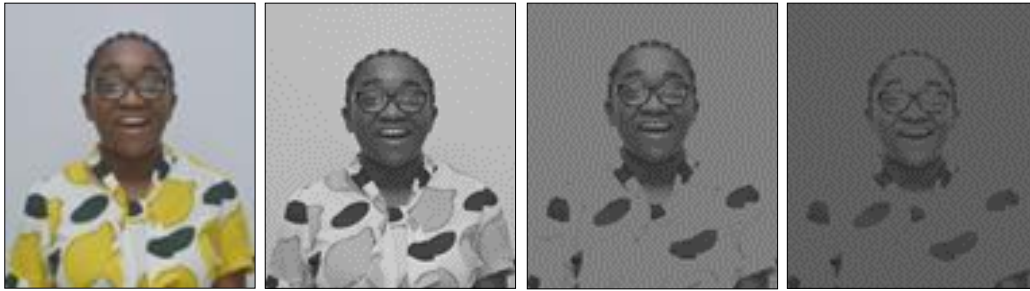


Fig 2: First Sample of an individual image in color form and in grayscale 255, 127 and 95 intensity values

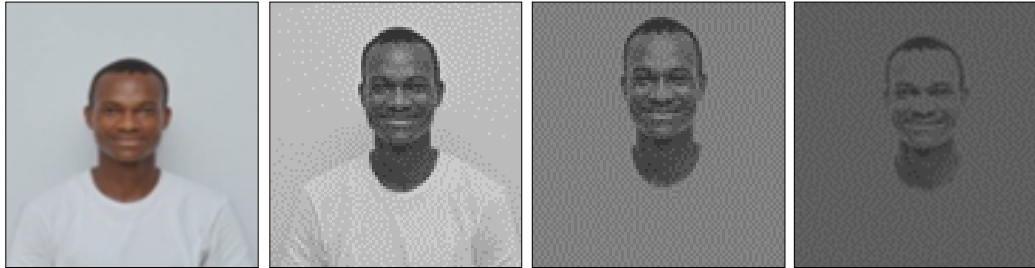


Fig 3: Second Sample of an individual image in color form and in grayscale 255, 127 and 95 intensity values

2. Evaluation of Preprocessing Time

To assess the preprocessing time associated with different grayscale conversion intensity values (255, 127, and 95), each dataset underwent multiple trials of preprocessing, and the time taken for each trial was recorded. The preprocessing time was measured from the moment the color images were loaded to the completion of the grayscale conversion process.

For the dataset with an intensity value of 255, the average preprocessing time was observed to be approximately 0.036 seconds. This relatively higher preprocessing time can be attributed to the full intensity range utilized in the grayscale conversion, which necessitates more extensive calculations and processing steps to transform the color images into grayscale. Despite the longer processing time, the resulting grayscale images retained maximum detail and clarity, demonstrating the trade-off between processing time and image quality.

In contrast, the datasets with intensity values of 127 and 95 exhibited shorter average preprocessing times of approximately 0.02 and 0.017 seconds, respectively. The reduced intensity ranges in these datasets contributed to faster processing times by simplifying the conversion process and requiring fewer computational resources. While the preprocessing time was significantly lower compared to the 255 intensity dataset, the grayscale images generated from these datasets displayed varying levels of detail and

contrast, reflecting the compromise between processing speed and image fidelity.

Overall, the results of the preprocessing time evaluation highlight the importance of considering intensity value selection in grayscale conversion for facial recognition applications. By understanding the relationship between intensity values and preprocessing time, researchers can optimize computational efficiency while maintaining acceptable levels of image quality for real-time facial recognition systems.

3. Results of Face Detection

The face detection process was conducted on the grayscale images generated from the three grayscale conversion schemes. Across all datasets, the face detection algorithm successfully identified and localized facial regions within the images. Following the successful detection of faces, the next step involved cropping the detected facial regions from the grayscale images. The cropping process facilitated the extraction of relevant facial features for subsequent analysis and classification tasks. Figure 4 and Figure 5 below shows samples of visual representation of the face detected images in G-255 (Grayscale converted dataset of 255 intensity value, G-127 (Grayscale converted dataset of 127 intensity value and G-95 (Grayscale converted dataset of 95 intensity value.



Fig 4: First Sample of Face detected Images in G-255, G-127 and G-95

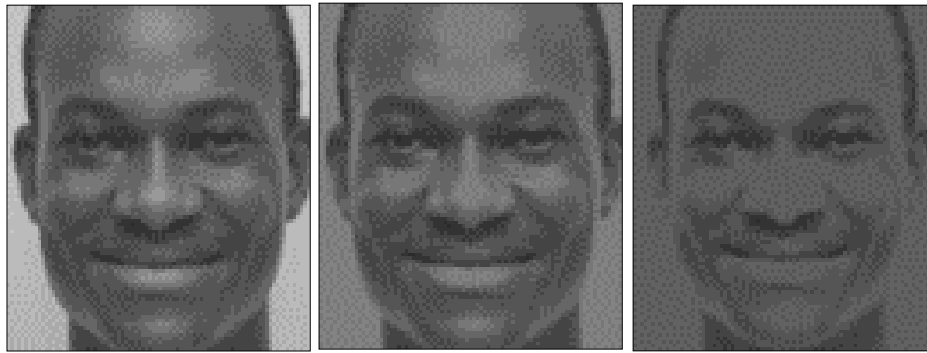


Fig 5: Second Sample of Face detected Images in G-255, G-127 and G-95

4. Feature Extraction Discussion

Feature extraction played a critical role in enhancing the performance of classification algorithms for facial recognition. By transforming raw image data into meaningful feature descriptors, feature extraction reduces the dimensionality of the data while preserving relevant information essential for accurate classification. The extracted features, represented as histograms, capture

unique facial characteristics and patterns that are discriminative for different individuals.

5. Results of Model Evaluation

The results indicate the performance of the SVM and KNN classification algorithms on the three grayscale datasets.

1. Accuracies achieved by SVM and KNN for each grayscale intensity value (255, 127, and 95)

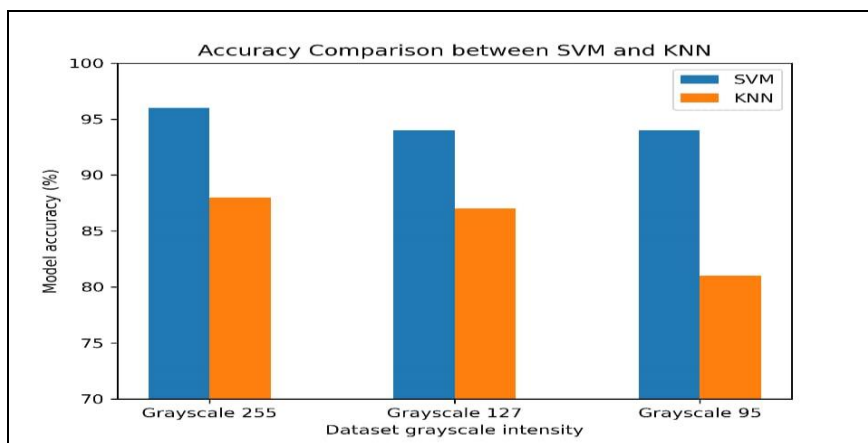


Fig 6: Graph of Accuracy comparison between SVM and KNN

The grouped bar plot in Fig 6 provides a visual representation of the accuracies achieved by SVM and KNN for each grayscale intensity value (255, 127, and 95). Each intensity value is represented by two bars: one indicating the accuracy of SVM and the other representing the accuracy of KNN. Analyzing the plot, it's evident that SVM and KNN achieve varying levels of accuracy across different grayscale intensity values. For the 255 intensity value, SVM demonstrates an accuracy of 96.88%, while KNN achieves 88.54%. Similarly, for the 127 intensity value, SVM achieves an accuracy of 94.79%, and KNN achieves 87.50%. Lastly, for the 95 intensity value, SVM achieves an accuracy of 94.79%, and KNN achieves 81.25%.

Comparing the accuracies of SVM and KNN within each grayscale intensity value, we observe that SVM consistently outperforms KNN across all intensity values. The highest accuracy achieved by SVM is observed for the 255 intensity value, followed by the 127 intensity value, and then the 95 intensity value. In contrast, KNN consistently demonstrates lower accuracies compared to SVM for all intensity values. These findings have implications for model selection in real-world facial recognition applications.

2. Evaluation of Model Accuracies and Preprocessing time of the three datasets

Table 1: Accuracy and Preprocessing time of the datasets

Datasets	Accuracy	Preprocessing time (s)
G-255	SVM: 96.88% KNN: 88.54%	0.036
G-127	SVM: 94.79% KNN: 87.50%	0.020
G-95	SVM: 94.79% KNN: 81.25%	0.017

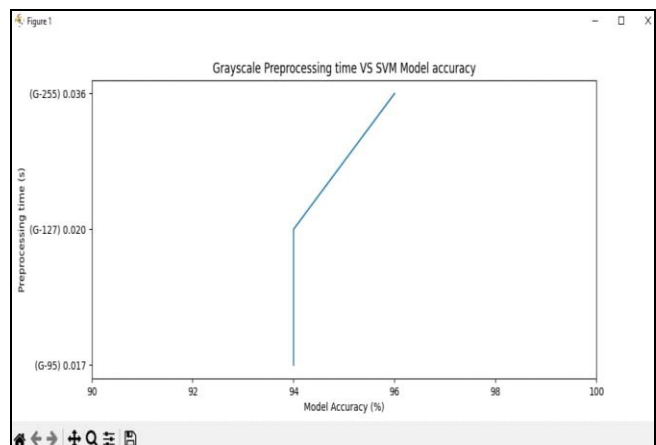


Fig 7: Graph of Preprocessing time versus SVM accuracy

The line plot in Fig 7 illustrates the relationship between SVM accuracy and preprocessing time for each grayscale intensity value: Upon examination of the line plot, it becomes apparent that there is a discernible trend between SVM accuracy and preprocessing time across different grayscale intensity values.

The results reveal that as the preprocessing time decreases, there is a corresponding variation in SVM accuracy. Specifically, lower grayscale intensity values, which correspond to shorter preprocessing times, exhibit relatively high SVM accuracy compared to higher intensity values with longer preprocessing times.

For instance, for the G-255 dataset, which has a preprocessing time of approximately 0.036 seconds, the SVM accuracy is approximately 96.88%. Similarly, for the G-127 dataset with a preprocessing time of approximately 0.02 seconds, the SVM accuracy is approximately 94.79%.

Finally, for the G-95 dataset with a preprocessing time of approximately 0.017 seconds, the SVM accuracy is also approximately 94.79%.

This finding holds significant implications for real-time facial recognition applications, particularly in scenarios where minimizing preprocessing time is crucial. The observed trend suggests that selecting grayscale intensity values associated with shorter preprocessing times can lead to satisfactory SVM accuracy while enhancing the responsiveness of real-time facial recognition systems. Based on the analysis, the 127 intensity value emerges as a favorable choice due to its balanced combination of shorter preprocessing time and satisfactory SVM accuracy. Therefore, it is recommended to consider employing the 127 intensity value in real-time facial recognition systems to achieve optimal performance in terms of both accuracy and processing speed.

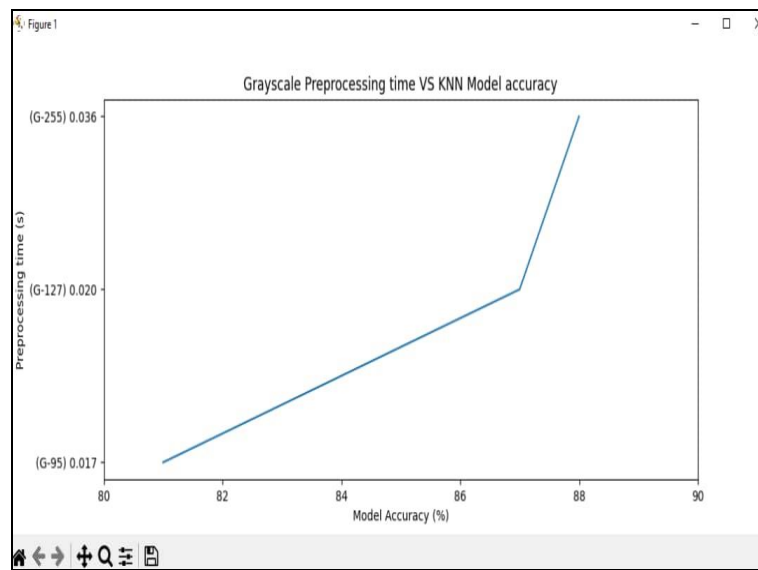


Fig 8: Graph of Preprocessing time versus KNN Accuracy

The line plot in Fig 8 depicts the relationship between KNN accuracy and preprocessing time for each grayscale intensity value. Analysis of the line plot reveals a correlation between KNN accuracy and preprocessing time across different grayscale intensity values.

Similar to the SVM results, the trend observed in KNN accuracy corresponds to the variations in preprocessing time. Lower grayscale intensity values with shorter preprocessing times exhibit relatively higher KNN accuracy

compared to higher intensity values with longer preprocessing times. For example, in the G-255 dataset, where preprocessing time is approximately 0.036 seconds, the KNN accuracy is approximately 88.54%. In contrast, for the G-127 dataset with a preprocessing time of approximately 0.02 seconds, the KNN accuracy is approximately 87.50%. Lastly, for the G-95 dataset with a preprocessing time of approximately 0.017 seconds, the KNN accuracy is approximately 81.25%.

Table 2: Performance Comparison of our study with existing literature

Study	Dataset	Model	Accuracy (%)	Pre- Processing Time (s)
Hivit <i>et al.</i> , 2019	Extended CK+	SVM KNN	93.53% 79.97%	No report
Handy <i>et al.</i> , 2021	Self created Dataset	SVM KNN	95.2% 96.2%	No report
Anisha <i>et al.</i> , 2022	Self created Dataset	SVM KNN	88.0% 98.6%	No report
Kumar <i>et al.</i> , 2019	ORL Dataset	KNN	90.35%	No report
Our study	G-255 Dataset	SVM KNN	96.88% 88.54%	0.036
Our study	G-127 Dataset	SVM KNN	94.79% 87.50%	0.020
Our study	G-95 Dataset	SVM KNN	94.79% 81.25%	0.017

6. Performance Comparison of our study with existing literatures

Our examination of the literature revealed both notable similarities and differences between our findings and those reported in previous studies. Across various research endeavors, including Hivi *et al.* (2019), Handy *et al.* (2021), Anisha *et al.* (2022), Kumar *et al.* (2019), SVM and KNN models were commonly employed for facial recognition tasks. While our study aligns with this trend by utilizing SVM and KNN classifiers, our focus on datasets created with lower grayscale intensity values distinguishes our approach from prior works. In terms of accuracy, our study demonstrates competitive performance compared to existing literature. For instance, Hivi *et al.* (2019) reported SVM and KNN accuracies of 93.53% and 79.97%, respectively. Similarly, Handy *et al.* (2021) achieved SVM and KNN accuracies of 96.2% and 95.2%, respectively. Our results, particularly for the 127 and 95 grayscale intensity datasets, showcase accuracies that are comparable to or even exceed those reported in the literature.

However, it's essential to note that our study introduces a novel aspect by exploring the impact of lower grayscale intensity values on dataset creation. This innovation is reflected in the performance of our models, with the 127 and 95 grayscale intensity datasets demonstrating high accuracy levels alongside shorter preprocessing times. This finding deviates from the conventional use of higher grayscale intensity values in facial recognition systems and underscores the potential benefits of adopting alternative approaches.

Furthermore, while previous studies often relied on standardized datasets such as the Extended Cohn-Kanade (CK+) dataset or the ORL (Olivetti Research Laboratory) dataset, our research leveraged internally collected datasets. Our datasets were meticulously created and prepared to ensure optimal performance in real-world scenarios.

In conclusion, our study contributes valuable insights into the performance of facial recognition systems, showcasing competitive accuracy levels while pioneering the utilization of lower grayscale intensity values. These findings offer promising prospects for enhancing the efficiency and effectiveness of real-time facial recognition systems, paving the way for future advancements in the field.

7. The Optimal Dataset Choice for enhanced balance and performance

The SVM accuracy for both conversions of G-127 and G-95 Datasets have approximately a 2.16% decrease compared to the conversion of 255. The KNN accuracy for the conversion of 127 has a decrease of approximately 1.17%, while the conversion of 95 has a larger decrease of approximately 8.24%. Also, for the percentage difference in preprocessing time for the conversion of 127 compared to 255 is approximately 44.44%, and for the conversion of 95 compared to 255 is approximately 52.78%.

Here are some reasons why G-127 outperforms both G-95 and G-255 in terms of achieving a balance between accuracy and preprocessing time:

- 1. Percentage Difference Analysis:** By comparing the percentage differences in both accuracy and preprocessing time between the grayscale conversion values of 127 and 255, we gain valuable insights into the trade-offs involved in selecting the optimal conversion value. The percentage difference in

accuracy between 127 and 255 reveals a slight decrease in accuracy for 127 across both SVM and KNN models (approximately 2% for SVM and 1% for KNN). However, the percentage difference in preprocessing time between 127 and 255 indicates a significant improvement in preprocessing efficiency for 127, with a decrease of approximately 44.44%.

- 2. Balancing Accuracy and Efficiency:** While accuracy is paramount for facial recognition systems, real-time applications like attendance tracking require computational efficiency to process data quickly and accurately. The grayscale conversion value of 127 strikes a better balance between these two factors compared to 255.
- 3. Optimized Performance:** Despite the slight decrease in accuracy, the conversion value of 127 maintains high accuracy levels that are still suitable for reliable attendance tracking. Moreover, its substantial improvement in preprocessing efficiency ensures faster processing of facial images, leading to quicker identification and tracking of individuals in real-time scenarios.
- 4. Scalability and Practicality:** In real-world applications, scalability and practicality are essential considerations. The optimized performance of the conversion value of 127 enhances the scalability of facial recognition systems by reducing computational overhead and improving response times, even when dealing with large volumes of data.

Conclusion

In conclusion, this research project aimed to optimize facial recognition datasets by evaluating and validating the performance of grayscale conversion intensity values on preprocessing time and accuracy for an optimal approach to enhance the reliability and efficiency of real-time attendance tracking at CITE. The study involved data collection, preprocessing, model training, and evaluation. Through the experiments conducted, it was found that lower grayscale intensity values, specifically 127 and 95, provided a better balance between preprocessing time and accuracy compared to the conventional 255 intensity value. This finding suggests that utilizing lower grayscale intensity values can offer improved efficiency without compromising recognition accuracy, aligning with the aim of enhancing real-time attendance tracking systems.

Furthermore, the comparison with existing literature revealed that the performance of the developed models and datasets was comparable to or even superior to previous studies. Notably, the 127 intensity value demonstrated a particularly promising balance for real-time facial recognition systems, highlighting its potential for practical applications. This optimized approach promises efficiency, accuracy, and reliability in real-time facial recognition systems, providing valuable contributions to both academic research and practical applications.

References

1. Trushna R, Shriya K, Mahesh H, Shubham W, Prof. AD W. Real Time Student Attendance System Using Face Recognition. *Int J Innov Res Technol*, 2021, 8(1).

2. Murthy KS, Kumar KK, Priya S, Shreya S, Yashaswini J. Facial recognition-based attendance system with student live location tracking. JETIR, 2023, 10(6).
3. Pandey AK, Kumar A, Abdul Aleem D. Smart attendance system using face recognition. YMER, 2023, 22(04).
4. Akash S, Shreya B, Abhishek G. Automated Attendance System with Face Recognition. Int J Eng Appl Sci Technol, 2021;5(12):233-4.
5. Gupta V, Srivastava A, Varshney BC. Attendance management system using facial recognition. YMER, 2023, 22(05).
6. Hivi DI, Abdulrazzaq MB. Facial expression classification based on SVM, KNN, and MLP classifiers, 2019.
7. Handy P, Oktaria K. Real-time Triplet Loss Embedding Face Recognition for Authentication Student Attendance Records System Framework. JOIV Int J Inform Vis, 2021;5(2):155.
8. Anisha S, Reddy GVSS. Automated facial recognition for class attendance. Int J Recent Dev Sci Technol, 2022, 6(6).
9. Kumar SS, Varun SA, Sahoo PK, Eswaran K. Class room attendance system using KNN. IJCST, 2019, 10(1).