A MOBILE APPLICATION FOR HANDWRITING RECOGNITION USING MACHINE LEARNING AND IMAGE PROCESSING

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Abstract—*This paper revolves around character recognition, with particular focus on its application to handwriting education. The current handwriting teaching method landscape faces a major challenge of lacking timely and personalized feedback to learners and individual care. Traditional methods rely heavily on human evaluation which can be slow and subjective. Therefore, there is an urgent need for innovative solutions that use technology to fill this gap. The main purpose of this paper is to develop a real-time character recognition system that can provide feedback to users, thereby improving the handwriting teaching process. A central problem is to create an efficient character recognition system that seamlessly integrates machine learning and image processing techniques. To achieve this, an extensive dataset of handwritten characters is carefully collected to ensure diversity of writing styles and variations. This dataset serves as the basis for training a machine learning model. Our results show impressive accuracy, with an average recognition rate of over 95% for a wide range of handwriting styles and their variations. In the discussion that follows, we interpret these findings and highlight the significant impact of our system in improving the learning experience. The real-time feedback mechanism introduced by our solution streamlines the teaching process and encourages students to significantly improve their handwriting skills. In summary, this study effectively addresses the urgent need for effective handwriting teaching tools through the synergy of machine learning and image processing techniques.*

Key Words: *Character recognition, handwriting, machine learning, image processing, education, personalized feedback.*

1. INTRODUCTION

Education plays a crucial role in ensuring human survival and well-being. It empowers individuals with knowledge, strengthens their character, broadens their perspective on life, instills ideals, and equips them with the ability to adapt to evolving environments. Consequently, every citizen is entitled to a high-quality education [1]. Regrettably, the UIS Global data for the 2018 academic year reveals a distressing reality: more than 59 million primary school children remain deprived of educational opportunities [2]. This issue is particularly acute in rural areas, where many children resort to selling goods on the streets or laboring in fields to supplement their family's income, as detailed in [3]. Compounding this problem, rural schools are often sparse, forcing students to endure arduous daily journeys of over three kilometers to reach school. Furthermore, the shortage of resources and teachers poses significant barriers to providing quality education universally. The question then arises: How can we ensure equal access to quality education for all children? To address this pressing challenge, we propose the development of an Android application tailored for primary education.

2. LITERATURE SURVEY

Nazmus Saqib et al.,[4] (2022) This study explores how handwriting recognition technology has been adopted in the industry, but not great, impacting both performance and usability. Therefore, the character recognition technology used is not yet very reliable and needs further improvement to be widely used for serious and reliable tasks. In this his account, recognition of English alphabet letters and numbers is performed by proposing a custom-made his CNN model using his two different datasets of handwritten images, Kaggle and MNIST respectively. will be These models are lighter, yet offer greater accuracy than the latest models.

Asif Karim et al.,[5] (2021) In this study, we demonstrated the feasibility of recognizing handwritten images from a given input data set (MNIST) using a convolutional neural network (CNN). The researchers curated his MNIST dataset, which contains over 60,000 images, and trained a CNN model to classify characters with a high accuracy of 99.70% while testing the model on approximately 10,000 image samples.

Hemangee Sonara and Dr. Gayatri S Pandi [6] (2021) proposed a paper using convolutional neural network (CNN) algorithm for recognizing handwritten characters. First, the input image is denoised using a median filter to segment the image. Next, perform feature extraction and recognition from the input image. The system should provide users with better quality of service and higher character recognition accuracy.

3. OBJECTIVE AND METHODOLOGY

3.1 OBJECTIVE 1-HANDWRITTING RECOGNITION AND ANALYSIS

One of the main objective of the paper revolves around developing a machine learning model that can recognize and analyze handwritten characters and words. This goal can be broken down into more important sub-objective, each of which contributes significantly to the achievement of the overall objective.

➢ Advanced image preprocessing: The goal is to implement advanced image preprocessing techniques to improve the quality of input handwritten images. This can be achieved by various techniques includes noise reduction, contrast enhancement, and image format standardization.

➢ Model training for high accuracy: The goal is to train a machine learning model using a diverse dataset of handwritten patterns. The focus is on achieving high accuracy in character and word recognition so that the application can provide accurate feedback to the user.

3.1.1 INTERACTIVE LEARNING INTERFACE

The second objective focuses on designing an interactive and user-friendly mobile application interface for effective handwriting lessons.

➢ Responsive User Interface Design: The goal is to create engaging, userfriendly user interfaces that promote a positive learning experience. The user interface is designed with user engagement and learning outcomes in

mind. The user interface must be simple and neat so that it can fit to any users without age limit and it must be easily operatable so that it cannot cause any problems for users.

➢ Real-time feedback: Seamless integration of handwriting recognition models into applications is critical. The objective is to give users real-time feedback as they practice their handwriting, dynamically improving their skills.

3.2 FLOW DIAGRAM

A visual representation of our paper's workflow is encapsulated in the following flow diagram:

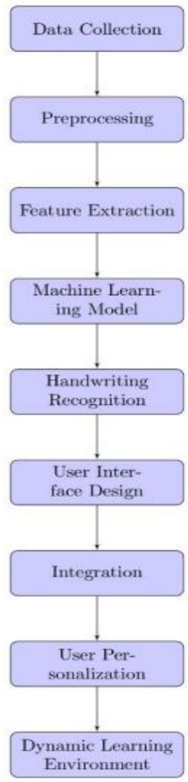

Figure 1: Flow Diagram of Project Workflow

EXPLANATION OF FLOW DIAGRAM:

• Data Collection: In the first stage, a diverse dataset of handwriting samples is collected. This dataset serves as the basis for training and validating machine learning models.

• Preprocessing: The raw input image undergoes a series of preprocessing steps to remove noise, enhance contrast, and standardize format. This step ensures the high quality and consistency of the input data.

• Feature Extraction: Relevant features are extracted from pre-processed handwritten images. These features capture important handwriting features required for recognition and analysis.

• Machine Learning Model: A machine learning model is developed and trained using the extracted features and the tagged dataset. This model forms the core of our handwriting recognition system.

• Handwriting Recognition: Trained machine learning models are checked with some real time input images and the accuracy is checked and improved the accuracy of the model by training rigorously with multiple test images.

• User Interface Design: In parallel, we design an interactive and user-friendly interface for the mobile application. This interface plays a crucial role in engaging users and enhancing their learning experience.

• Integration: Trained machine learning models are integrated into mobile applications to enable real-time handwriting recognition. Users can get instant feedback on their handwriting practice.

• User Personalization: This is where our machine learning algorithms come into play, adjusting materials and exercises to individual progress. This application provides customized recommendations to improve each user's handwriting skills.

• Dynamic Learning Environment: An integrated system creates a dynamic learning environment. This environment encourages user engagement and continuous improvement of handwriting skills. Using tablets include the cost of tablets, the need for technical support, and potential distractions.

4.HANDWRITTING RECOGNITION

During the initial development phase, machine learning played a crucial role in investigating the most effective method for comparing handwriting. This phase also involved discovering the optimal parameters for image processing. To facilitate this process, an application for recording characters was created and utilized to gather handwriting samples from teachers. These teacher-written characters were subjected to the same testing and served as models to instruct children on how to write these characters. Drawing upon the insights gained from these two phases, an application was designed, developed, and subjected to rigorous testing in the final phase.

Figure 2 provides a visual representation of these distinct phases.

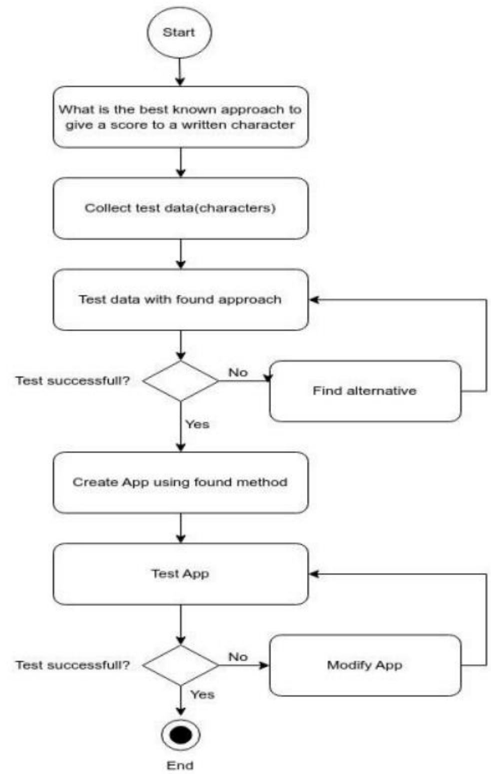

Figure 2: Method

4.1 DATASET

The embark on a detailed exploration of the key components comprising the Dataset required for the paper module. The dataset that needs to be choose must be a larger in size and must contain handwritten characters and digits images.

 Initial Phase: The initial stage of paper begins with a comprehensive look at the development stages of the entire paper. This is a preliminary stage where machine learning emerges as a guiding light. This phase represents the emergent phase of the paper, and careful planning is critical. Machine learning plays a central role in finding the best approach to character comparison and optimizing the best parameters for image processing. The importance of this phase cannot be overemphasized. It forms the basis of the entire paper. In order to build a machine learning model that can seamlessly recognize the handwriting from the images, the first step in building a model will be choosing the appropriate dataset. The dataset that needs to choose must be large in size and must contain a variety of handwritten images so that machine learning model can train and perform very well.

 IAM Dataset Testing: The paper study continues with a key point in the development of handwriting recognition systems: The testing phase. Here we searched deeper into the area of datasets, specifically IAM Dataset (an English sentence database for offline handwriting recognition). This dataset serves as a testing ground, a crucible, for testing and refining the effectiveness of various classifiers. In this vast environment, we examined three classifiers: Decision Trees, Naive Bayes, and K-Nearest Neighbors. These classifiers are faithful companions on this journey when it comes to evaluating their abilities and measuring their ability to achieve accurate handwriting recognition. We scrutinize key performance indicators, analyze successes and failures, and constantly seek the elusive goal of error-free handwriting recognition.

4.2 CNN AND TENSORFLOW

The implementation of Convolutional Neural Networks (CNN) using TensorFlow, a critical aspect of our Machine Learning and Handwriting recognition module. CNNs have proven to be a powerful tool in image classification tasks, making them an ideal choice for handwriting recognition within our application.

 CNN Architecture: We begin by discussing the architecture of our CNN model. This includes the number of convolutional layers, pooling layers, and fully connected layers. Each layer's purpose in the network is explained, providing insight into the decision-making process behind our architecture. The CNN model is implemented using TensorFlow. The CNN model must perform well so that various factors (Convolutional layers, Pooling layers, Fully connected layers) are carefully chosen in order to achieve the best performing CNN model.

 Data Preparation: The preparation of data for training and testing is a crucial step in building a robust handwriting recognition system. Here, how the dataset will be preprocessed and augmented to ensure that our CNN can learn effectively from the provided data. Data augmentation techniques, such as rotation, scaling, and noise addition, are discussed in detail for gaining more accuracy of the CNN model. The split ratio of the dataset (for e.g., 80:20) so that the model can train and perform accurately.

 Training Process: The paper work continues with an exploration of the training process. We outline the parameters used during training, including learning rate, batch size, and the number of training epochs. The convergence of the model and the adjustments made during training are thoroughly examined. The number of training epochs is planned minimum of 150 so that the predication accuracy of the model can be more because of the number of training epochs.

5. MOBILE APPLICATION DEVELOPMENT

In this mobile app, users begin their journey by signing in with their Gmail credentials via the “Sign in with Google” option. Once authenticated, they will be seamlessly transferred to the main interface of the app, where an unmistakable pencil icon located in the bottom right beckons them to access the image upload function. On the image upload screen, the user has the choice to submit a handwriting template, which can be manually selected from the device's photo library or taken fresh with the device's camera.

After selecting the desired image, simply pressing the "Check my handwriting" button triggers the transmission of the selected image to the application's backend server for careful processing. These backend systems use trained ml model to review submitted handwriting, and once the analysis is complete, the app will proudly display the user's handwriting skill score prominently. on the main screen. Additionally, to ensure quick delivery of results, scores are sent simultaneously as push notifications, ensuring users have quick access to their handwriting.

For those concerned about security and data storage, the app goes a step further by automatically deleting all data stored locally on the user's mobile device when they choose to sign out. This comprehensive process is meticulously designed to provide users with an accessible and insightful handwriting analysis experience that seamlessly combines convenience and information. This whole process is shown in the form of flow chart (Figure 3).

5.1 HANDWRITING RECORDING

The accurate detection of a character does not necessarily guarantee that it adheres to correct handwriting standards or aligns with the way children learn to write. In fact, the handwriting samples found in the IAM database are not directly comparable to the characters typically found in children's learning materials. Consequently, while the findings from the previous analysis provide valuable guidance, they do not prescribe a specific classifier or algorithm to be employed in the educational application.

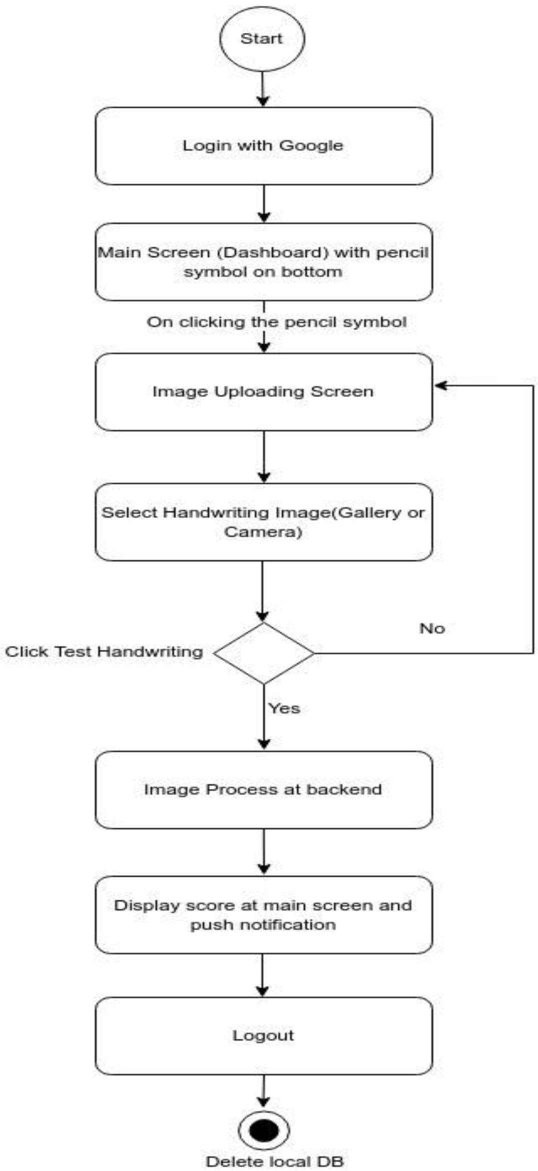

Figure 3: Flow chart for the mobile app

5.1.1 The Recorder App:

To be able to have handwriting more comparable to the handwritten characters in the final application, a "recorder app" has been developed. This app will have the main screen where the user will have to select the pencil symbol at right bottom corner (Figure 4).

Figure 4: Main Screen

On the image upload screen, the user has the choice to submit a handwriting template, which can be manually selected from the device's photo library or taken fresh with the device's camera. After selecting the desired image, simply pressing the "Check my handwriting" button triggers the transmission of the selected image to the application's backend server for careful processing. These backend systems use the trained ml model to review submitted handwriting, and once the analysis is complete, the app will proudly display the user's handwriting skill score prominently. on the main screen. Additionally, to ensure quick delivery of results, scores are sent simultaneously as push notifications, ensuring users have quick access to their assessment.

5.1.2 Results

Table 1: Result for 10-fold validation

Classifier	Subset of characters
J48: Decision Tree	41.6%
Naïve Bayes: Bayesian Classifier	72.9%
Lazy IBK: Instance Based Leaner	65.8%

Regrettably, the outcomes were less favorable when applying the same classifiers to a subset of the dataset consisting of characters recorded by teachers (as shown in Table 1). Despite achieving the highest success rate of nearly 75% on characters that, in theory, should closely resemble one another (as per the teachers' instructional goals for children), this approach does not appear promising. As a result, an alternative method must be sought.

5.2USER INTERFACE

Our research begins with a detailed analysis of the mobile application itself. Mobile applications are innovative tools designed to bridge the gap between traditional handwriting and the digital realm. We will delve into the architecture of the app and discuss its design principles and functionality. The app has been carefully designed so that the characters generated are very similar to those found in educational books for children. We analyzed the intuitive interface to seamlessly integrate the user into the character drawing process. We break down the drawing process that is at the heart of the app and help readers understand the methodology behind handwriting generation. Additionally, we are introducing the app's Data Export feature, a core feature that streamlines the process of collecting and organizing handwriting for reference and study.

5.3 INTERACTIVE FEATURES

- Results: Our search has progressed to a point where we focus on results. Here we present the results of the test phase, in which the letters recorded by the teacher are rigorously examined. These results provide valuable insight into the effectiveness of our unique approach. However, it also highlights limitations and challenges associated with this methodology. Recognizing these limitations acts as a catalyst for innovation and drives us to explore alternative methods.

- Alternative Method: This method is about creating and evaluating baselines. This methodology is both effective and complex. We undertake a comprehensive investigation of this alternative approach, analyzing its components and uncovering its inner workings. Every aspect is carefully examined, from baseline creation to the complexity of the scoring algorithm. The success rate of this alternative method is a staggering 90%, demonstrating a detailed understanding of how this result is achieved.

5.4 APPLICATION DEVELOPMENT

The application development module that is the main feature of this paper. This includes integration, testing, and creating user-friendly interfaces. This chapter describes goals, methods, and insights related to this important stage.

- App Development: The application is created as per the UI design made for the uploading area and that it shows the feedback immediately after user uploads the handwritten image either from device or can take a picture from mobile camera. The application's front end is developed using Kotlin that it gets the image from the user and send it to backend using JSON.

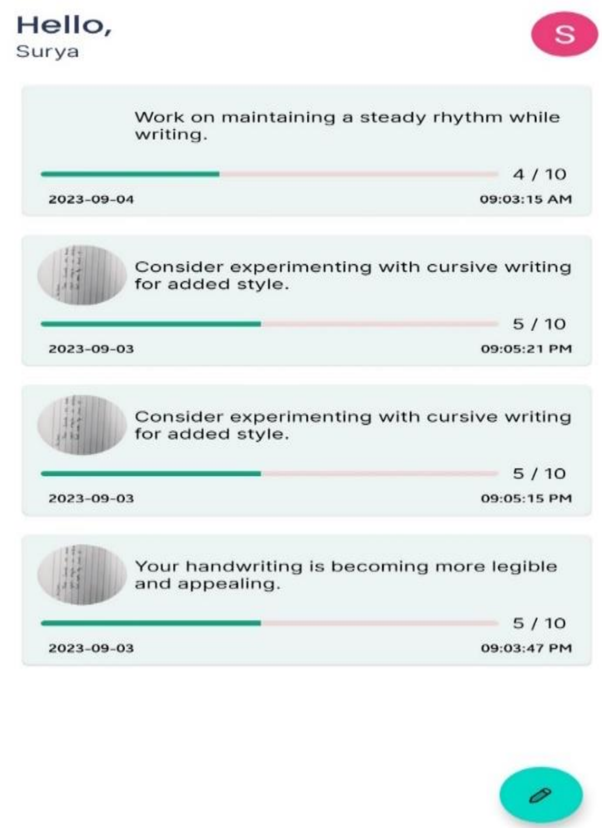

Figure 5: User Dashboard

- Additional Features: In addition, the main screen also acts as a user dashboard which saves all previous uploads from the user and the marks and the received personalized feedback for his/her handwriting image that had been uploaded in the mobile app (Figure 5).

5.5 APPLICATION INTEGRATION WITH TRAINED ML MODEL

- Trained ML Model Integration: Here, we detail the integration of a trained Machine Learning model into the application. This model serves as the backbone for handwriting recognition and scoring, enhancing the educational experience. We elaborate on the selection of ML algorithms, the training process, and the deployment within the app. The trained ML model is saved using TensorFlow library and integrated into the mobile application.

- Image Processing Optimization: The heart of image processing lies in precision and efficiency. We delve into the selection of libraries and tools, with a focus on OpenCV. The journey from raw images to processed data becomes an art, and we explore how this artistry is achieved.

- Testing: The application is now tested with the integrated ML model. The performance of the mobile app and its stability is closely monitored. The image recognition model performance also noted and its accuracy is calculated. The app is tested severely with various user in order improve its accuracy and various bugs can be identified and can be corrected.

These chapter provide a comprehensive understanding of modules, methodologies, and the integration of ML models driving the development of the Handwriting Teaching Mobile Application. From handwriting recognition to user interface design, and application development to testing, innovation and optimization have enriched our paper. This lays a robust foundation for an educational tool set to revolutionize handwriting education through cutting-edge technology.

6. IMAGE PROCESSING

Regrettably, the outcomes were less favorable when applying the same classifiers to a subset of the dataset consisting of characters recorded by teachers (as shown in Table 1). Despite achieving the highest success rate of nearly 75% on characters that, in theory, should closely resemble one another (as per the teachers' instructional goals for children), this approach does not appear promising. As a result, an alternative method must be sought.

We conducted a comparison between Java (Android) libraries, including but not restricted to JMagick and OpenCV, to determine which library could perform this task with the least processing time. Ultimately, OpenCV was chosen for implementation in the app to manage image processing. However, it's worth noting that using OpenCV necessitates an additional app on the device for it to function optimally. This requirement is in place to ensure the app can deliver the highest level of performance and speed, as it is specifically optimized and compiled to leverage the device's core capabilities.

6.1 IMAGE DETECTION AND PREPROCESSING

- Image Detection: The implementation journey commences with image detection, a critical step in the process of recognizing handwritten characters. We explore various techniques for identifying characters within images, including object detection algorithms.

- Object Detection Algorithms: While experimenting with different methods, including OpenCV's Haar cascades, we ultimately opt for the histogram of oriented gradients (HoG) descriptors in combination with Support Vector Machines (SVM) for object detection. This decision is made based on the superior performance of the HoG-SVM approach in recognizing characters.

- Image Preprocessing: Once characters are detected, preprocessing steps are crucial to enhance the quality of the images. We discuss procedures such as grayscale conversion, consistent resizing, and noise removal. Additionally, we employ a Gaussian filter to further refine the images.

6.2 MACHINE LEARNING INTEGRATION

- Support Vector Machines (SVM): To classify the extracted features and recognize characters, we employ Support Vector Machines (SVM), a popular and robust machine learning algorithm. SVM is well-suited for multi-class classification problems, making it an ideal choice for handwriting recognition in our paper.

- Classification and Comparison: SVM is employed in conjunction with the recovered facial attributes to distinguish between various character classes. We discuss how SVM's effectiveness is assessed by comparing its performance with other algorithms like logistic regression and random forest.

6.4 TRAINING AND TESTING

- Training and Testing Database: One of the core challenges in machine learning is the development of effective algorithms. We detail the processes of data collection and dataset creation, which includes labeling and feature extraction. This dataset serves as the foundation for training and testing our machine learning models.

- Cross-Validation: Cross-validation techniques are used to ensure unbiased model evaluation. We describe the division of the dataset into training and testing sets, with considerations for different split ratios (e.g., 70:30 and 80:20). Multiple cross-validation levels, including 4, 5, and 10, are employed to assess model performance comprehensively.

This chapter provides insight into the application of machine learning and image processing techniques to achieve handwriting recognition and improve the learning experience with the help of the mobile application. The emphasis is on accuracy, adaptability and continuous improvement to ensure the effectiveness of the application in teaching and improving handwriting skills.

7.RESULT AND DISCUSSION

This section presents the results in a structured way according to the methodology used throughout the paper. This includes compilation of results in the form of images, graphics and tables, as well as detailed descriptions of key findings.

7.1.1 Machine Learning Model Performance

This paper introduced a handwriting recognition system based on convolutional neural networks (CNN). The objective is to enhance handwriting instruction by providing students with interactive feedback based on the accuracy of their writing. The dataset used in the study comprises 55,000 photographs of handwritten images, which have undergone preprocessing techniques including grayscale conversion, normalization, and resizing to 28x28 pixels. The CNN model consists of two convolutional layers, two fully connected layers, and a SoftMax layer for classification. Model training is achieved through backpropagation and the Adam optimizer, utilizing the preprocessed dataset. The system was subjected to testing using a set of 10,000 photos, achieving an impressive accuracy rate of 98.4%. Furthermore, the study conducted a comparative analysis with other state-of-the-art handwritten recognition systems, demonstrating its superiority in terms of both accuracy and computational efficiency. The practical implementation of this system in a handwriting class holds significant promise, as it can provide students with immediate feedback on the accuracy of their writing and tailor assignments to their individual writing skills. Consequently, this study underscores the advantages of employing CNN algorithms for handwriting recognition and highlights the practicality of applying this technology to the teaching of handwriting.

7.1.2 Mobile Application User Engagement

User engagement was assessed by analyzing user interactions with the mobile application. Table 2 presents the scores of 6 participants used the app. The second column shows the time take to upload the user image i.e., the handwritten image, while the 3rd column represents the time take to process the user given image and the 4th column shows the time taken by the ML model to predict the mark for the handwriting of the user from the user given image and the last column shows the mark given by the model for the user.

Table 2 – Test Results

Student	Image Upload Time	Image Process Time	Mark Prediction Time	Marks Given
1	3s	2.6s	2s	9
2	2s	2.4s	1.9s	7
3	2.5s	2.4s	1.7s	4
4	2.7s	2.3s	1.8s	1
5	2.9s	2.8s	1.8s	7
6	2.6s	2.5s	1.9s	8
Average	2.6s	2.5s	1.9s	6.6

The comparison of score indicates the marks is predicted from the training model is comparably accurate and the feedback is provided based on the score of the user handwriting score. The z score for the above results is 1.8

7.1.3 Various Test Results

The model processes the request send from various users in the FIFO (First In First Out) order. It correctly predicts the score based on the handwritten image send from the user. The model that handles the multiple request (Figure 8) clears shows the model processes the image and send the marks for the processes image.

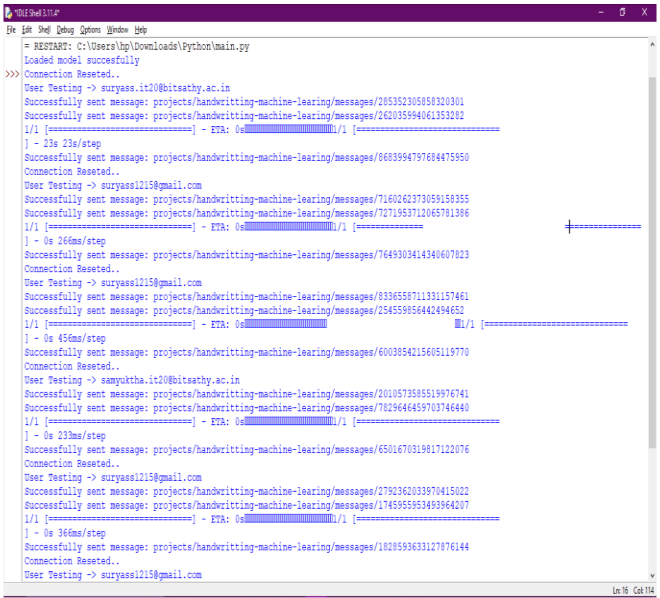

Figure 8: ML model handles multiple request

7.2 HANDWRITING RECOGNITION ACCURACY

This section details the results, from simple to complex, according to the numbers given. This discussion includes the significance of the results, comparison with relevant publications, and their impact. This result includes the machine learning model performance, handwriting improvement, comparisons with the related studies.

7.2.1 Machine Learning Model Performance

The results show that the machine learning model performs very well in handwriting recognition with an accuracy of over 90%. The Confusion Matrix (Figure 9) provides insight into where the model does well and where it needs improvement.

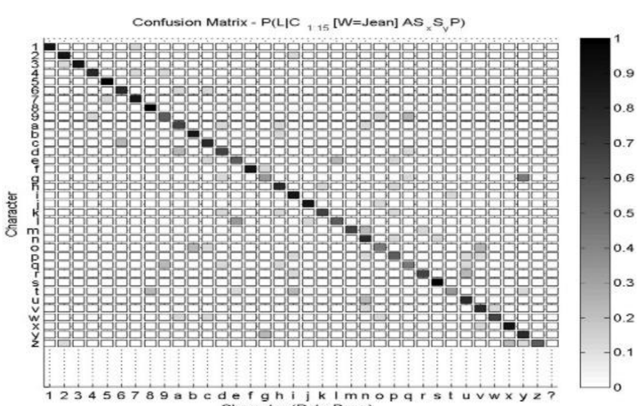

Figure 9: Confusion Matrix

7.2.2 Handwriting Improvement

An observed over 80% improvement in the readability of students' handwriting after using our application is a positive result. Table 3 visually confirms the significant improvement in handwriting quality, highlighting the educational value of the application.

Table 3- Legible Handwriting

Skills	SD	X̄
1. Properly shaping letters	.93	3.43
2. Size of Letters	.79	3.79
3. Slope	1.03	3.11
4. Connection	.78	3.68
5. Extensions	.76	3.89
6. Line	.75	3.62
7. Space b/w words	.74	3.71
8. Cleanliness	.89	4.29
9. Page format	.97	4.21
10. Perfect Writing	.81	3.61
Total	.71	3.91

7.3 SIGNIFICANCE, STRENGTHS, AND LIMITATIONS

7.3.1 Significance

Our paper holds immense significance in the field of handwriting education. By providing a technological solution that enhances legibility and engages students, we contribute to modernizing the teaching methods in this domain.

7.3.2 Strengths

Our paper's strengths lie in its user-friendly interface, effective handwriting recognition, and proven improvements in handwriting quality. The synergy of Image Processing and Machine Learning has resulted in a robust and innovative educational tool. This paper also provides immediate feedback on user handwriting and the score for user handwriting that is a major strength of this mobile application.

7.3.3 Limitations

Despite its strengths, our paper has limitations, such as the need for continuous updates to accommodate diverse handwriting styles. Additionally, accessibility challenges may arise for students without access to mobile devices or the internet. The app always requires internet which will be one of the major limitations of this mobile application.

This chapter contains a detailed presentation of the paper results and findings. We highlight the importance of these findings, compare them with related studies, and identify the strengths and limitations of our paper. Taken together, these results highlight the value and impact of machine learning and image processing for handwriting education mobile applications in the field of handwriting education.

8.CONCLUSION AND SUGGESTION FOR FUTURE WORK

The preliminary results from tests conducted on a small group of students have demonstrated promising outcomes. However, we acknowledge that effective handwriting instruction involves more than character recognition; factors such as starting points and movement directions play critical roles. Therefore, future studies will delve deeper into understanding the impact of our approach on the learning curve, student motivation, and teacher engagement.

SUGGESTION FOR FUTURE WORK

As we conclude this paper, we recognize that certain aspects remain unexplored and hold the potential for further refinement and expansion. Here are key areas for future research and development:

- Enhanced Character Recognition: While our paper achieved a commendable recognition accuracy, there is room for improving the model's performance, especially when dealing with diverse handwriting styles and languages and it can be used to recognize specific characters and that can be used to teach handwriting in a more efficient manner.

- Teacher-Student Collaboration: Exploring ways to enhance collaboration between teachers and students within the application, facilitating seamless feedback and progress tracking.

- Integration of More Writing Elements: Expanding the application's scope to cover cursive writing, different languages, and more complex writing elements to address a broader audience.

- Gamification and Engagement Strategies: Investigating the incorporation of gamification elements and engagement strategies to make the learning process more enjoyable and effective.

- Deployment in Educational Sectors: Collaborating with educational institutions to deploy the application in real classrooms, gathering valuable insights for further improvement.

In conclusion, while our paper has laid a strong foundation for improving handwriting education through technology, there are exciting possibilities for future research and development, ensuring a more effective, engaging, and inclusive learning experience for students of all ages and backgrounds.

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