CNN Based Handwritten Prescription Recognition for Medicine Identification
Final Year Design Project

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled "**CNN Based Handwritten Prescription Recognition for Medicine Identification**," submitted by **Most.Afrin Jahan Asa**, **ID**: 211-15-14594 and **Bristy Rani Dash**, **ID**: 211-15-14612 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on January 12 ,2025.

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We hereby declare that this project has been done by us under the supervision of Md. Sazzadur Ahamed , Assistant Professor, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Doctors frequently write prescriptions in unreadable handwriting due to the growing demands on healthcare workers, making it difficult to correctly identify the names of the recommended medications. Patients are greatly affected by this problem since they could find it difficult to comprehend the prescription drugs they are meant to take. Because doctors' handwriting styles vary so much, no method has been able to completely address the challenge of recognizing handwritten medicine names despite multiple tries. In this work, we present a solution that uses machine learning techniques to identify handwritten pharmaceutical names. The system is implemented through a mobile application that captures prescription medicine images, preprocesses them with techniques such as image crop, and resizing, gray scaling, normalization and then classifies the images using a Convolutional Neural Network (CNN). The proposed system is evaluated using a dataset of handwritten medicine names, with the CNN model demonstrating an accuracy of 83.53%. By reducing medicine name misinterpretations, this technology helps patients and pharmacists ensure proper prescription consumption.

Keywords: Handwritten medicine name recognition, CNN, CRNN, Deep learning, AI, Medical data, Accuracy, F1-score, Precision, Recall.

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Chapter 1

Introduction

This chapter provides an overview of the research, presenting the background, problem statement, and motivation behind the study of this research. It describes the goals of the study and presents the approach taken to overcome the difficulties in recognizing handwritten prescriptions. The chapter also covers the study's expected results and its importance in enhancing patient safety and healthcare accuracy. The chapter's structure is intended to help readers comprehend the objectives, methodology, and significance of the research.

1.1 Introduction

The readability of doctor's handwritten prescriptions is still a major problem in many nations, including Bangladesh. Unreadable handwriting for drug names may be detrimental to a patient's health. This is especially an issue in countries, where prescriptions are still often handwritten. Even though printed prescriptions are obligatory in several wealthy countries like the United States and the UK as well as a few countries in Europe, many underdeveloped countries still carry the burden of poor handwriting. The US "Electronic Prescribing of Controlled Substances" rule has resulted in over a 50% lower prescription errors [1] and the UK NHS has achieved 40% improvement in medication accuracy [2]. In countries like Bangladesh, handwritten prescriptions are still common. According to a survey conducted by the Bangladesh Medical Association (BMA), about 80% of Bangladeshi prescriptions are written by hand, and many of them are difficult to read because of illegible handwriting [3]. It is difficult to guarantee accuracy and clarity in prescription records without a national digital prescription system. In Bangladesh, more than 5,000 deaths are attributed to pharmaceutical errors caused by illegible prescriptions every year, and thousands more are associated with adverse drug events and difficulties caused by misreading prescriptions. According to a World Health Organization (WHO) research, around 10% of hospital admissions in impoverished nations like Bangladesh are caused by pharmaceutical errors [4]. Additionally, more than 85% of prescriptions are written by hand with inadequate healthcare facilities, which greatly raises the possibility of such errors [5]. It is becoming more and more important to build AI-based systems that can automatically recognize and understand handwritten pharmaceutical names from prescriptions in light of these difficulties. This study suggests an artificial intelligence (AI) model that can identify medication names from handwritten prescriptions, which is a major advancement over the manual recognition approach. This strategy seeks to improve medication accuracy, lower human error, and ultimately increase patient safety by tackling the problem of unreadable handwriting.

1.2 Motivation

The motivation for this research arises from the pressing need to improve the security and effectiveness of healthcare systems, especially in nations where handwritten prescriptions are still widely used, is what spurred this study. The problem is considerably worse in Bangladesh, where a significant section of the populace still uses handwritten prescriptions, which can result in misunderstandings, confusion, and even death. The problems with handwritten medical prescriptions are not limited to bad handwriting; they are a serious issue that has an everyday impact on healthcare results. We have seen personally how a simple prescription may be the difference between life and death for patients, doctors, and pharmacists in Bangladesh. The grave repercussions of illegible handwriting in medical prescriptions are shown by several real-life situations that we encounter on a daily basis. A notable case occurred in 1999 when a Texas jury awarded $450,000 to the family of a patient who died after a pharmacist misread a doctor's handwritten prescription. The pharmacist gave out Plendil (felodipine), a drug for hypertension, instead of the Isordil (isosorbide dinitrate) that the cardiologist had recommended for angina because of the pharmacist's illegible handwriting. The patient died from a heart attack as a result of this mistake, which caused a 16% overdose of Plendil [6]. This is a typical situation in many healthcare facilities in Bangladesh, where the lack of printed or computerized prescriptions leads to preventable medical mistakes. Pharmacists sometimes misunderstand prescriptions due to unclear acronyms or handwriting that is difficult to read. This problem is particularly severe in rural areas, where many medical facilities lack the funding necessary for contemporary diagnostic equipment. In order to address the problem of unreadable handwriting, this study suggests using artificial intelligence. Incorporating artificial intelligence (AI) into handwritten prescriptions can automate the process of identifying and analyzing prescription data, guaranteeing that patients receive the right drug. This research attempts to solve this issue in order to improve patient safety, lower healthcare expenses, and aid in the modernization of healthcare systems in underdeveloped nations. This AI-powered approach may ultimately prove to be an essential instrument in reducing prescription errors, raising the standard of care, and guaranteeing that patients get the care they require without taking needless risks.

1.3 Objectives

I. To develop a model capable of recognizing handwritten medicine names, making it accessible and helpful for pharmacists and the general public.

II. To tackle key challenges in the medical sector by using a specialized prescription dataset for accurate medicine name recognition, reducing errors in medication identification.

III. To evaluate and present the best-performing model, providing a foundation for future advancements in related applications.

1.4 Methodology

In this study, medicine images are gathered as part of the data collection process. To ensure consistency and improve model performance, the images are preprocessed through several steps. This includes converting them to grayscale, normalizing the pixel values, and resizing them to a standard dimension. After preprocessing, the images are fed into a model designed to extract. We explore different model architectures to identify the one that performs best in recognizing medicine names from handwritten prescriptions. To further enhance accuracy and ensure the model's effectiveness in real-world medical applications.

1.5 Project Outcome

The outcome of this research will be the development of an AI-based deep learning model capable of accurately recognizing handwritten medication names. By automating the interpretation of illegible handwriting, the model will reduce medication errors, ensuring patients receive the correct medication. This will significantly improve patient safety and minimize the risk of adverse drug reactions and hospitalizations. Additionally, the solution will support healthcare professionals, particularly in country regions where handwritten prescriptions are still common, by providing a more efficient and reliable tool for medicine recognition. Ultimately, the model will contribute healthcare sector and improving the overall quality of patient care, while paving the way for future innovations in digitized healthcare systems. The project also offers the potential for future expansion to recognize additional information and making it adaptable for broader applications in medical transcription.

1.6 Organization of the Report

There are six chapters in the report. The study is introduced in Chapter 1, which also discusses the goals, anticipated results, and the rationale for the investigation. Additionally, we explain the issue, list the subjects that were investigated, and talk about the research methods and their possible implications. Chapter 2 explores the fundamental ideas, defining important words, analyzing relevant literature, and pointing up areas where earlier research was lacking. In Chapter 3, we describe the dataset used, provide an overview of the study methodology, and go into detail about the preprocessing methods used, such as gamma correction. We also examine the deep learning techniques used and describe the data splitting procedure. The evaluation methods used are the main topic of Chapter 4, which is followed by a thorough performance analysis. This chapter contains model analysis, graphics, and a detailed explanation of the outcomes. We discuss the project's sustainability in Chapter 5, taking into account its effects on society and the environment. We also discuss financial analysis, project management, and solving difficult engineering problems. Chapter 6 concludes the study, lists its limitations, and makes recommendations for further research.

Chapter 2

Background

The research's fundamental background is given in this chapter, which also reviews important ideas, previous research, and difficulties in handwritten prescription recognition. It looks at the importance of the issue, the technologies at play, and the shortcomings of the existing solutions that this study seeks to fill.

2.1 Introduction

The background information required to comprehend the context of handwritten prescription recognition and its significance in enhancing healthcare systems is provided in this section. It talks about the difficulties caused by unreadable handwriting on prescription drugs, such as the possibility of drug mistakes, and investigates how artificial intelligence (AI) can help with these problems. This section lays the groundwork for the suggested AI-based solution, which intends to improve prescription interpretation accuracy and efficiency in order to improve patient safety and healthcare outcomes, by examining current technologies and approaches.

2.2 Literature Review

Table 2.1: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings
Hassan et al.	2021	Handwritten Medical Prescription Recognition Using CNN and OCR	CNN for classification and OCR for post-processing with pre-processing techniques.	Achieved training 70% and 50% testing accuracy in recognizing medicine names and created their own dataset, which included pictures of handwritten prescriptions. There is no description of the total number of prescriptions filled.

Dinuka Kulathunga et al.	2020	PatientCare: Patient Assistive Tool with Automatic Hand-written Prescription Reader	OCR with preprocessing, CNN-RNN (LSTM) for recognition, Custom NER for text categorization	Achieved 64%-70% accuracy in handwriting recognition and 95%-98% accuracy in medical categorization like blood report.
W.R.A.D. Wijewardena	2019	Medical Prescription Identification Solution	First, CNN extracts feature from the images, which RNN uses to identify the content.	Achieved 63.10% accuracy and it is Knowledge Base Matching.
Seerat Rani et al.	2022	Recognition of Handwritten Medical Prescription Using Signature Verification Techniques	Here, the authors have correctly recognized handwritten medical prescriptions using a signature-based verification technique. Doctors use a pen on a pad to first write the prescriptions in this suggested method, and the system stores features. Here, the author has tested their suggested method on nine distinct users using four distinct classifiers: SVM, decision tree, naïve bayes, and gradient boost.	SVM has the highest overall accuracy of 84% among all the tested classifiers. Here, the writers have gathered information from two users on 24 medication names. The primary drawback of their suggested methodology is that the dataset they utilized to test it is extremely small. Additionally, they have worked on PDAs using styluses, which are not frequently used by doctors to write their prescriptions, rather than directly working on handwritten medical prescriptions on paper.

Pavithiran G. et al.	2022	Doctor's Handwritten Prescription Recognition System in Multi-Language Using Deep Learning	CNN, RNN, and LSTM for handwritten text recognition; Fuzzy Search and Market Basket Analysis for optimization	Achieved 74% accuracy using SRP data augmentation with Bidirectional LSTM; integrated multi-language support.
Peilun Wu et al.	2018	Handwritten Medical Prescription Recognition Using Deep Learning	Integrated multi-classifier combining CNN, PCA, KNN, and voting mechanism	Achieved 99.1% recognition accuracy and its limitation is it based on Chinese medicine prescriptions.
Tavish Jain et al.	2021	Handwriting Recognition for Medical Prescriptions using a CNN-Bi-LSTM Model	CNN for feature extraction, Bi-LSTM for sequential prediction, CTC for decoding, augmented IAM dataset	Achieved high accuracy not mentioned the presentence. And it uses IAM dataset not medical dataset. In prescription text recognition with bias towards medical terms to improve prediction.
Shaira Tabassum et al.	2022	An Online Cursive Handwritten Medical Words Recognition System	Data augmentation (RSS: Rotate, Shift, Stretch), Bidirectional LSTM for sequence prediction	Achieved 92.0% average accuracy with data augmentation. Taken online cursive handwriting.
Tavneet Singh et al.	2023	A Comprehensive Review on the Techniques Used for Recognizing Handwritten Medical Prescriptions	Reviewed ML/DL approaches like CRNN, SVM, OCR post-processing, dataset-specific techniques	Highlighted CRNN as the most effective model; emphasized the lack of open-source datasets for medical prescriptions. Not mentioned accuracy in this paper.

Lovely Joy Fajardo et al.	2019	Doctor’s Cursive Handwriting Recognition System Using Deep Learning	CRNN with model-based normalization scheme; combined CNN for feature extraction and LSTM for sequence prediction	Achieved 76% training accuracy, 72% validation accuracy. 1800 images and12 medicine names only.
Tabassum et al.	2022	Recognition of Doctors’ Cursive Handwritten Medical Words by using Bidirectional LSTM and SRP Data Augmentation .	Here, the acquired data was first examined and preprocessed by the researchers, who then applied their suggested data argumentation technique to the preprocessed data, increasing the dataset's sample size. Next, using their suggested LSTM model.	“Handwritten Medical term Corpus” which includes 17,431 samples. The average accuracy without data augmentation is 73.4% whereas the accuracy with SRP data expansion is 89.5%.Here have taken doctor’s handwriting entries using a Tablet and only take 11 medicine.
Makarand Shahade et al.	2023	Convolutional Neural Networks for Handwritten Text Recognition of Medical Prescriptions	CNN with preprocessing techniques including normalization, resizing, and binarization for text recognition	Achieved 89% training accuracy and 70% testing accuracy for recognizing medicine names from handwritten prescriptions.
Aanthu et al.	2018	Digitalization of Medical Prescription.	The writers have put forth a three-part system here. The doctor uses a stylus to write their prescription on the PDA in the first part, which the system interprets as an image. Afterward, the image is preprocessed using various techniques	Proposed model accuracy 99.5%. Instead of testing their model on real handwritten prescription data, the authors used a generic MINIST dataset that only included handwritten numbers, but the

			and sent to the cloud in the second part, where it is fed to a CRNN model that transforms the handwritten text into digital text	genuine prescription also included text.
E.Kamalanaban et al.	2018	Medicine Box: Doctor’s Prescription Recognition Using Deep Machine Learning	Here use pre-train model CNN and RNN. In order to validate the medication name at the backend and transform the handwritten text to digital text, the model and string-matching operation compare the output text with the custom repository.	Since the authors haven't explicitly stated the accuracy they attained in their work, they have simply used a graph to illustrate the accuracy, hence the model's accuracy is only about 35%. One disadvantage of their suggested strategy is that the IAM dataset, which the authors used to train their model, is extremely outdated and lacks the actual doctor handwriting data.
Dhar et al.	2021	HP_DocPres: a method for classifying printed and handwritten texts in doctor’s prescription	In the first step, the printed and handwritten text are localized to show where they are in the prescription. A random forest classifier is used in the second stage to classify the printed and handwritten text as either handwritten or printed.	Custom dataset specifically for this study that contains 11,340 samples of handwritten and printed text snippets. Here the actual medical prescriptions are only 11 and the authors of the study have applied various techniques to increase the dataset

Dhande & Kharat	2017	Character Recognition for Cursive English Handwriting to Recognize Medicine Name from Doctor's Prescription	Here, first doing pre-processing techniques, and then using vertical and horizontal projection techniques to separate the word and text-line segments from the preprocessed image, respectively, and finally they performed classification and recognition using SVM.	Here they have applied their proposed technique on 50 prescription samples. overall accuracy of 85%.

2.3 Gap Analysis

Many studies on handwritten medical prescription recognition face key limitations that hinder their scalability. Many studies have focused on handwritten medical prescription recognition using deep learning and OCR techniques, but there are several challenges and gaps in the current research. A key limitation is the dataset used in many of these studies. While some studies use custom datasets, they often do not provide sufficient details about the number of prescriptions or the diversity of handwriting styles. A medical prescription dataset of handwritten prescriptions was created by Hassan et al. in 2021 [7], who employed CNN for classification and OCR for post-processing. The model's generalizability is impacted by the unclear definition of the dataset's size and diversity. Furthermore, the comparatively low accuracy (70% training and 50% testing) indicates that preprocessing and model performance need to be improved. Using OCR in conjunction with preprocessing methods and a CNN-RNN (LSTM) model, Dinuka Kulathunga et al. in 2020 [8] achieved 64%–70% accuracy. Despite encouraging outcomes, their work has flaws that make it hard to determine the actual efficacy of their strategy, such as a tiny, non-diverse dataset. In their 2019 study, Roger Achkar et al. [10] achieved a remarkable 98% recognition accuracy for handwritten text. However, the model's robustness and practicality in real-world situations are called into question due to the lack of transparency around their training dataset and the failure to compare their technique with alternative methods. With an accuracy of 84%, Seerat Rani et al.[11] presented a signature verification method for handwritten prescription identification. However, the model's capacity to generalize is limited by the tiny size of their dataset only 24 medication names and the fact that there were only two users. Furthermore, the application of PDAs with styluses is limited to handwritten prescriptions on paper. In their review, Tavneet Singh et al. in 2023 [17] highlighted the efficacy of CRNN approaches for prescription recognition. They did, however, draw attention to a crucial gap in the field: the dearth of open-source medical prescription databases. Beautiful Joy Fajardo et al. in 2019 [18] used CNN-LSTM to recognize cursive handwriting with 76% accuracy. However, the intricacy of actual prescriptions is not reflected in their limited dataset (only 12 medication names).CNN with preprocessing techniques was utilized by Makarand Shahade et al. (2023) [10], achieved 89% accuracy during training. However, the model's 70% testing accuracy indicates that it needs more work and a larger, more varied dataset to increase generalizability. The practical implementation of the 99.5% accurate model proposed by Aanthu et al. (2018) [11] was limited because it was based on the MINIST dataset. Finally, a random forest classifier was presented by Dhar et al. (2021) [13] for the categorization of handwritten prescriptions. But with only 11 prescriptions, their sample is too tiny to make any significant inferences that can be used in the actual world.

2.4 Summary

The Introduction is covered in this chapter, along with background information on the difficulties in identifying handwritten prescriptions. The Literature Review, which summarizes current solutions and their shortcomings, is next presented. Lastly, the Gap Analysis pinpoints the shortcomings of the current systems and the areas where this study will concentrate on enhancing medicine detection

Chapter 3

Research Methodology

The approach used to create the handwritten medicine recognition system is described in this chapter. It covers every step of the procedure, including data collecting, picture preprocessing, model selection, and recognition model creation. It also covers the project design, task distribution, the rationale behind the selected methodology, alternative alternatives taken into consideration, and an overview of the procedures followed in carrying out the research.

3.1 Methodology

In this research, a comparative analysis was conducted to identify the most suitable model for handwritten medicine recognition. The models explored included, each chosen for their relevance and potential effectiveness in solving the problem. Preprocessing steps, including like resizing, normalization, gray scale conversion was applied to maintain the reliability and consistency of the data. Each model was trained using specific tools/libraries, with hyper parameter tuning performed to optimize performance. Evaluation metrics such as accuracy, precision, recall, F1-score were used to compare the performance of the models.

3.1.1 Overview

The planning and design process for the handwritten prescription recognition system is described in the overview. It involves outlining the needs for data collecting and system design, describing the problem, and comprehending the difficulties presented by handwritten medical prescriptions. The emphasis is on preprocessing methods, choosing the right model architecture, and assessing how well the system can increase prescription efficiency and accuracy in practical situations.

3.1.2 Proposed Methodology

Starting with data gathering and preprocessing, the suggested technique takes a methodical approach to creating the handwritten prescription recognition system. Medical professionals provide prescription photos, which have cursive handwriting. To standardize the input for the recognition model, these photos are subjected to preprocessing methods such resizing, normalization, and grayscale conversion. After preprocessing the prescription images,we tried multiple models to find the best-performing one and evaluate our model. The process is illustrated in the diagram figure 3.1.1 below, followed by an explanation of each step:

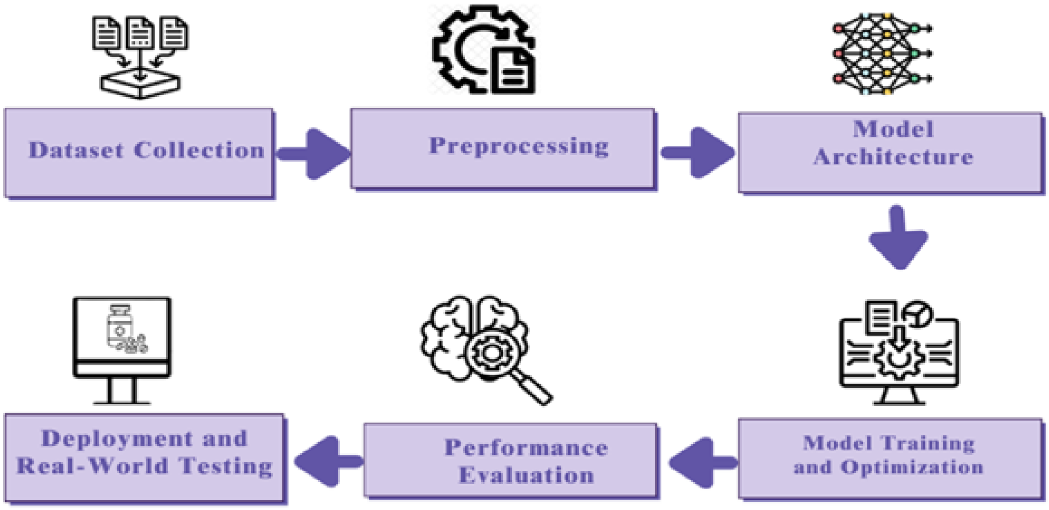

Figure 3.1.1: Methodology diagram

3.1.2.1 Data Collection Procedure

The first step involves gathering a specialized dataset containing handwritten prescriptions, specifically focusing on medicine names. The dataset for this research consists of 10842 images representing 78 different medicine names. To enhance the dataset's focus, we specifically targeted common medications that are widely prescribed for various conditions. These medications span multiple diseases and conditions, including allergies, respiratory issues, pain management, bacterial infections, fungal infections, and gastrointestinal disorders, among others. This dataset, covering a wide range of conditions, allows the recognition model to be trained on a varied collection of medicines. Mainly These images were gathered from a diverse set of sources, including doctors, medical students and researchers. We also used same type of 4000 images from Kaggle then marge all images for create our large number of datasets.

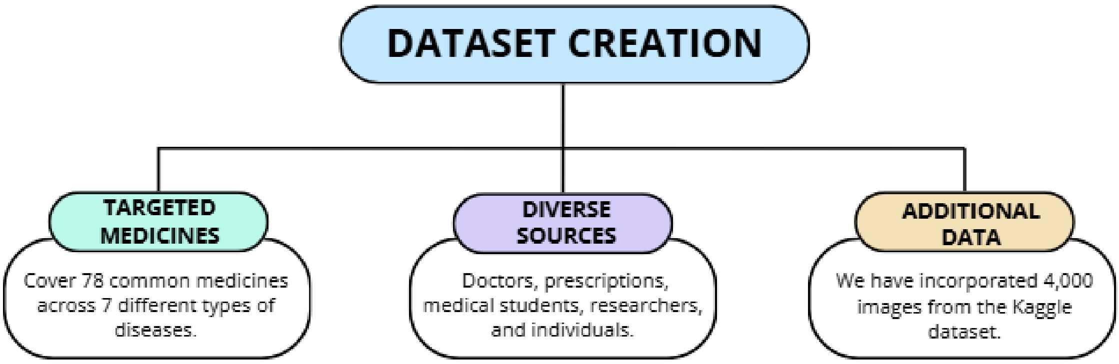

Figure 3.1.2.1: Dataset Collection Framework

Images also collected from raw prescriptions obtained directly from doctors and pharmacists, ensuring the authenticity and variety of handwritten data. From these prescriptions, similar medicine names were cropped and compiled for the dataset. Additionally, a small portion of the dataset includes handwriting samples from individuals with cursive handwriting, further increasing the diversity of the dataset. This variety in handwriting styles, along with the presence of real-world prescription data, allows the model to generalize better for medicine name recognition across different types of handwriting.

3.1.2.2 Dataset Preprocessing

A crucial phase in the data processing pipeline is data preparation, where the dataset is carefully organized and preprocessed for optimal use in model training. It enhances data quality, and standardizes input dimensions to ensure consistency across the dataset.

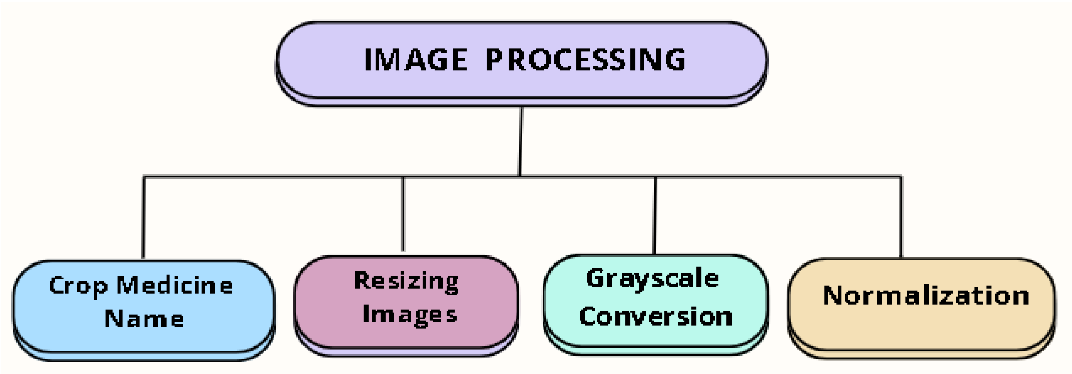

Figure 3.1.2.2: Preprocessing Technique

The medicine names in the dataset are manually cropped from the prescription images. After cropping, the images are resized to maintain a consistent input size. The images are then converted to gray scale, removing color information to simplify the data. Finally, the pixel values of the images are normalized, scaling them to a range between 0 and 1 to ensure consistent input for the model. This preprocessing ensures that the images are ready for efficient and accurate training for models.

Table 3.1.2.3: The Number of Images in Each Dataset

Dataset	Number of Images
Training	8346
Validation	1482
Testing	1014

3.2 Detailed Methodology and Design

In this research, several algorithms were trained in this study to recognize handwritten prescriptions. CNN (Convolutional Neural Network) and CRNN (Convolutional Recurrent Neural Network) were the two models that perform well from others. Along with EfficientNetV2S, ResNet, and SVM, pre-trained models like Easy OCR, Keras OCR, and PyTesseract were also used to testing how they works on this dataset. These models, however, demonstrated comparatively poorer accuracy in predicting unknown medications when trained on medicine dataset CNN gives better output from all other models in identifying unidentified medications. The research starts with data collection, followed by the data preprocessing steps. Several sample images from our dataset are shown in Figure 3.2.1

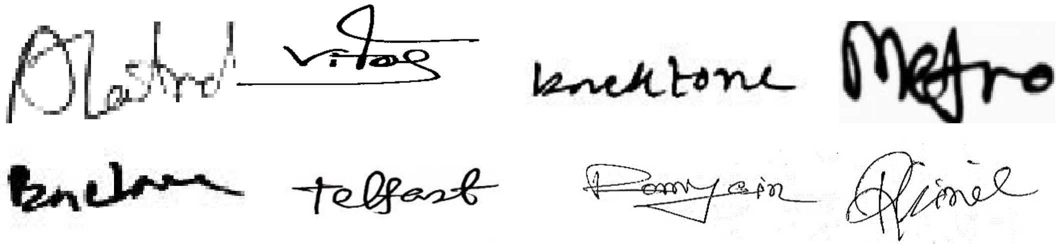

Figure 3.2.1: Sample Crop Data

A Convolutional Neural Network (CNN): In this research at first, used Convolutional Neural Network (CNN) that serves as an ideal model for recognizing and classifying medicine names from handwritten prescriptions. CNNs have shown remarkable success in image-based tasks due to their ability to automatically extract and learn spatial hierarchies of features, which makes them especially effective in recognizing complex and diverse handwriting styles.

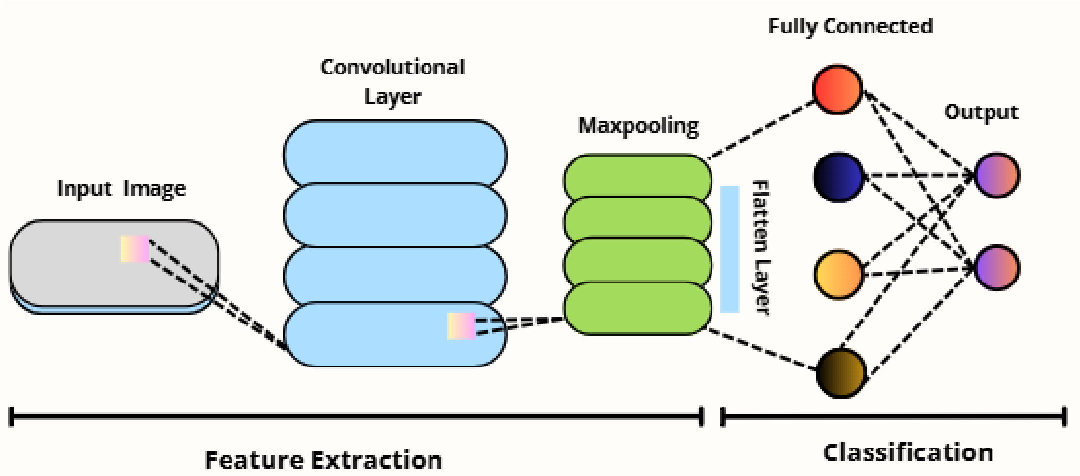

Figure 3.2.2: CNN Model Diagram

A CNN (Convolutional Neural Network) model was used in this study to identify medication names from pictures of handwritten prescriptions. Data collection was the first step in the procedure, and pictures of prescription drugs were kept in different files for testing, validation, and training. A CSV file with the matching labels (medicine names) was produced in addition to these pictures. The load_images_and_labels function was then used to preprocess the pictures, resizing them to 64x64 pixels and converting them to gray scale. To make sure the pixel values in these pictures were scaled between 0 and 1, they were normalized.

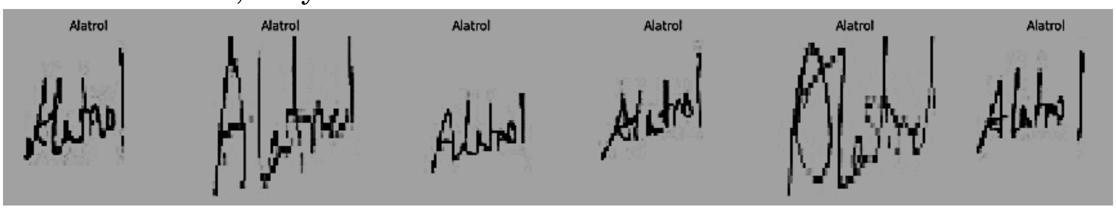

Figure 3.2.3: Labeled Medicine

The drug names were encoded into numerical labels using Label Encoder, and then to categorical were used to convert the labels to category form. The ImageDataGenerator was used to apply data augmentation for model training, adding rotation, translation, shearing, and zooming variables to the dataset to strengthen the model. A number of convolutional layers and max-pooling layers make up the CNN model itself, which aids in the extraction of features from the pictures. The output is flattened and then sent to fully connected layers for classification after going through convolutional layers. The SoftMax activation function is used in the final output layer to provide probability for every potential type of medication. The Adam optimizer and categorical cross-entropy loss were used to create the model. To maximize performance, early halting, learning rate reduction, and model checkpoint callbacks were used during the training process. When tested on the test set, the finished model demonstrated 83.53% of test accuracy in identifying the right medication names from the handwritten prescriptions.

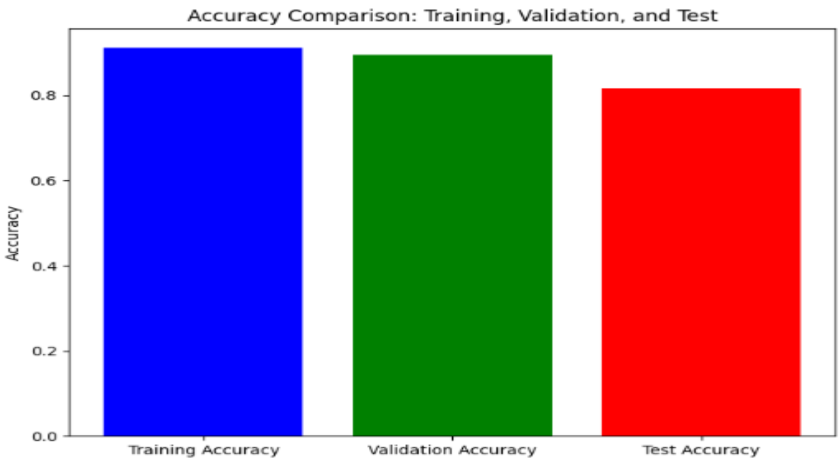

Figure 3.2.4: Accuracy Bar Chart

Convolutional Recurrent Neural Networks (CRNN): CRNN combine the sequence modeling skills of Recurrent Neural Networks (RNN) with the feature extraction capabilities of Convolutional Neural Networks (CNN). RNN layers the sequential character of the handwriting after CNN layers are used to extract features from prescription photos for handwritten drug name recognition. This hybrid design works especially well at identifying character sequences of different lengths in handwriting that is noisy and erratic. Additionally, CRNN are very adaptive to a variety of handwriting styles found in medical prescriptions since they may be trained end-to-end. This hybrid approach figure 3.2.5 refers the system to effectively recognize both the structure with CTC loss function and sequence of handwritten prescriptions.

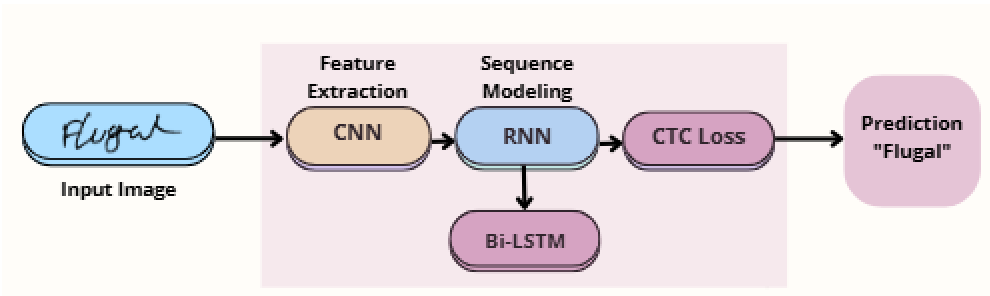

Figure 3.2.5: CRNN Basic Workflow Diagram

The CRNN model starts by receiving preprocessed images as input, where the images have already been resized, normalized, and converted to gray scale.

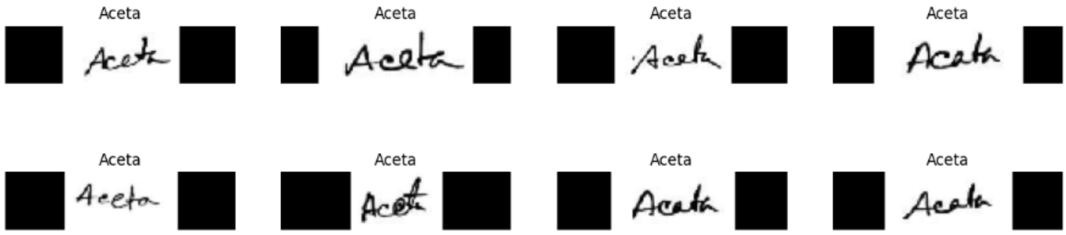

Figure 3.2.6: CRNN Labeled and Preprocessed Data

CNN layers, which serve as filters to extract significant elements like edges, forms, and textures from the handwriting, process the images. Bidirectional LSTMs in the RNN layers receive these attributes after which they process the character sequence both forward and backward, identifying connections between them. In order to anticipate the right character sequence without requiring precise alignment with labels, the model lastly employs CTC (Connectionist Temporal Classification) to align the predicted characters and manage irregular spacing or overlapping. After these steps, the CRNN outputs a sequence of characters, which is then decoded into readable text. This text corresponds to the recognized medicine names from the handwritten prescription. Throughout the process, the model learns to improve its predictions by minimizing the gap between the predicted and actual text during training. This model gives 70% accuracy for testing images.

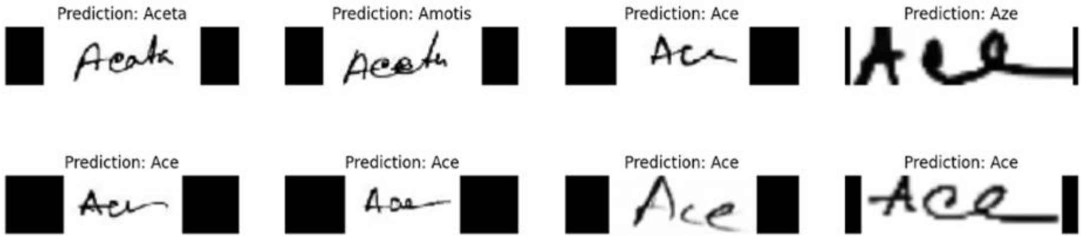

Figure 3.2.7: CRNN Actual Result and Predicted Result

EasyOCR: Pre-trained model has been used in this study to monitor and assess the output performance. Printed text in picture format can be successfully recognized by EasyOCR but it can't detect handwritten medicine properly. Using the strength of pre-trained models, EasyOCR is constructed by deep learning approaches, namely based on Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN).First, the image is acquired, and preprocessing techniques like grayscale conversion and binarization for improved contrast are applied. Pixels that aren't needed are eliminated using noise reduction. Then, using bounding boxes, EasyOCR's deep learning algorithm identifies text regions. The OCR engine extracts and transforms the text into a readable format after determining these regions. To fix any mistakes, the retrieved text is cleaned and post-processed. It achieved 56% In this model, the research did not achieve satisfactory accuracy, as shown by the incorrect outputs presented in Figure 3.2.8 below.

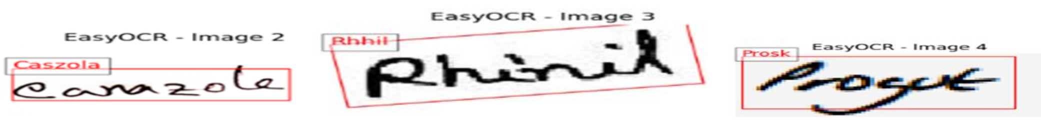

Figure 3.2.8: EasyOCR Predicted Result

MobileNetV2: In this model, a dataset of labeled medicine images input was gathered and divided into training, validation, and test sets into 3 different datasets for different users. In Preprocessing phase resizing images to 224x224 pixels, converting them to grayscale, and normalizing them using the MobileNetV2 preprocessing. Medicine names were encoded into numerical labels for classification. To enhance model performance, data augmentation was used ImageDataGenerator. The MobileNetV2 architecture is a pre-trained model that on ImageNet, was adapted for this task by adding a Conv2D layer to handle grayscale input and a custom classification head with a Global Average Pooling layer and a Dense layer with softmax activation. The model was trained using the Adam optimizer. Early stopping and learning rate reduction techniques were employed to optimize better training. The model was trained for 50 epochs and also evaluated on the test set using metrics like accuracy, F1-score, and a confusion matrix to analyze performance. All implementations were performed using TensorFlow and Keras, leveraging GPU acceleration for efficient computation. We found its accuracy 69% on our dataset.

PyTesseract: A Python package called PyTesseract serves as a wrapper for Google's open-source Tesseract OCR engine. Its purpose is to transform handwritten or printed language into machine-readable text from images. Tesseract OCR to extract text from prescription photos at the start of the procedure, which can take a while. The results are kept in a dictionary for efficiency, with the value being the relevant text output and the filename. Every image is represented as a row with its filename and matching text in a DataFrame once all of the OCR results have been collected. Unwanted items are then filtered out of this text to make it cleaner

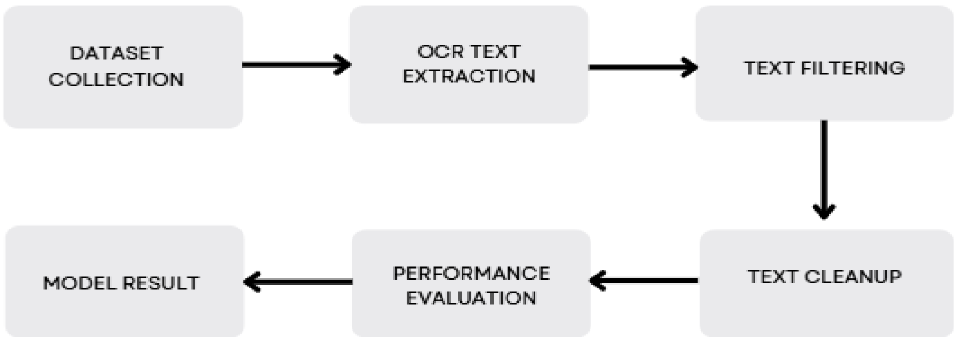

Figure 3.2.9: PyTesseract Workflow Diagram

For every image, clean text is then recombined. Lastly, the Jaro-Winkler method is used to determine a similarity score between the predicted and actual text in order to assess the OCR system's performance. This score provides a more detailed evaluation of the accuracy of the OCR model by indicating how closely the OCR output resembles the predicted identity. But this model does not provide satisfactory results for recognizing handwritten medicine names, as the accuracy level is 60%.

Support Vector Machine (SVM): One popular machine learning model for categorization applications, such as handwritten medicine recognition, is the Support Vector Machine (SVM). Using methods like flattening or extracting significant features, the handwritten images of medication names are preprocessed and transformed into feature vectors. After that, the SVM model receives these feature vectors and uses the learned decision boundary to attempt to categorize them into the appropriate categories. SVMs have shown less than ideal performance in handwritten medical recognition tasks, despite their strong performance in high-dimensional and smaller datasets. This model achieved 35% accuracy. styles vary widely and are complex, which reduces the effectiveness of feature extraction and restricts the model's capacity to generalize.

3.1 Project Plan

Table 3.3.1: Project Planning

Phase	Activities	Duration	Outcome
Phase 1: Problem Identification and Literature review	Identify the research problem, review existing literature, and define scope and objectives specific to handwritten prescription recognition.	2 weeks	Comprehensive understanding of the research problem and clear project goals.
Phase 2: Data Collection and Preprocessing	Collect handwritten prescription images, clean the data, Preprocessing works on the data.	12 weeks	A well-prepared and diverse dataset ready for experimentation.
Phase 3: Model Development	Model select, models testing and implement these deep learning models for prescription recognition.	8 weeks	Optimized and trained models for handwritten prescription recognition.
Phase 4: Model Evaluation and Analysis	Evaluate models using test/validation datasets and analyze performance	3 weeks	Detailed performance analysis and identification of the best model.
Phase 5: Result Visualization and Documentation	Visualize results, interpret findings, and document the research for handwritten prescription recognition.	2 weeks	Completed visualization and well-structured research documentation.
Phase 6: Finalization and Submission	Review the work, address feedback, and submit the final result.	2 weeks	Finalized and submitted project that meets academic standards.

3.1 Task Allocation

The project was cooperatively held between two individuals, who were given areas of expertise to be responsible for. Both are collected data from various sector. One of the partners carried out the literature review, the preprocessing of handwritten medicine images, and the implementation of the deep learning models. The other was the one who assessed the model performance, interpreted the results, made diagrams, and prepared the documentation. They both came together to polish the report, which they assured was the obligatory academic document and was completed within the stipulated timeline.

3.2 Summary

The Methodology section describes the approach for recognizing handwritten medicine names. It covers the process, including image preprocessing, feature extraction, model building. Testing many deep learning models and the section also includes the Project Plan, outlining key phases such as data collection, model development, and evaluation, as well as Task Allocation, specifying team responsibilities for efficient project execution.

Chapter 4

Implementation and Results

This chapter focuses on the development and evaluation of the handwritten medicine recognition system. It begins with Environment Setup, describing the tools and frameworks used, followed by Testing and Evaluation, which includes performance metrics and comparative analysis. The Results and Discussion section presents the findings from the system's implementation, highlighting its strengths and limitations. Finally, the Summary provides a concise overview of the chapter's key points.

4.1 Environment Setup

- GPU or Google Colab with GPU and CPU runtime for cloud-based acceleration.
- Windows 11 as the operating system.
- Python as the programming language.
- TensorFlow, PyTorch, and Keras for deep learning frameworks.
- OpenCV, NumPy, Pandas, and Matplotlib for image processing and data manipulation.
- Kaggle and VS Code for model training.
- Google Drive for file storage and access.
- Poco 5G for image gathering.
- Dependencies installed via pip or conda.

4.2 Comparative Analysis

The model analysis's efficacy is shown in Table 4.2.1. It is clear that using our dataset partially improved the performance of image recognition. Out of the several models that are now accessible, we must select the best one.

Table 4.2.1: Comparative Analysis

Citation	Dataset	Methodology	Accuracy
Hassan, E., Tarek, H., Hazem, M., Bahnacy, S., Shaheen, L., & Elashmwai, W. H.	After preprocessing techniques used CNN and OCR	Private dataset used contain medical prescription The total number of prescriptions taken is not described	Achieves an accuracy of 73% and the testing accuracy of 50%.

E. Kamalanaban, M. Gopinath, and S. Premkumar	CNN and RNN	IAM dataset Used	Accuracy achieved by their model is around 35%.
Peñaranda-Fajardo, N. M., et al., 2019	CRNN	Used 12 medicine name	Achieved overall accuracy 76%, F1-score of 84, Precision 80%, and a recall score of 89%
Ananthu, T., et al.2018	CRNN	Used MINIST dataset	Achieved 99.5%, Prescription on the PDA using a stylus
This Study	After preprocessing dataset used CNN, EasyOCR, MobileNetV2 KerasOCR, CRNN, SVM, PyTesseract, EfficientV2S	Handwritten Medicine Names used dataset Total 10842 medicine Images Training 8346 Validation 1482 Testing 1014 Augmentation doing in training time	Achieved 83.53% accuracy by CNN Achieved 56% by EasyOCR Achieved 69% by MobileNetV2 Achieved 70% by CRNN Model Achieved 35% by SVM Machine Learning Model Achieved 60% by PyTesseract Achieved 46% by EfficientV2S

4.1 Results and Discussion

Experiments showed that the CNN model achieved 83.53% test accuracy, Training accuracy 91.30%, Validation accuracy: 89.81% in recognizing medication names from handwritten prescriptions, that is better perform from others. Using data from outside sources that were not part of the training and testing datasets, the CNN model was also evaluated on handwritten medications in cursive script. The model demonstrated its capacity to generalize well to various handwriting styles by recognizing the pharmaceutical names, despite the difficulties presented by cursive handwriting.

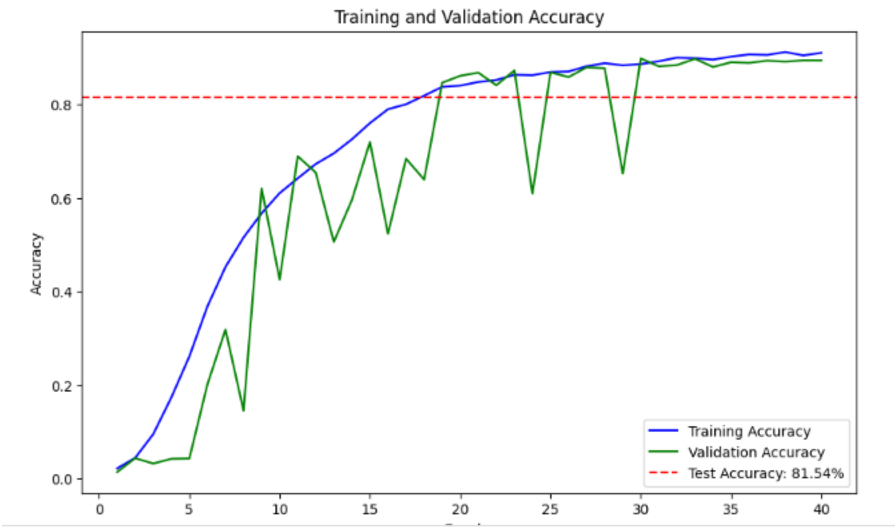

Figure 4.3.3: Training and Validation Accuracy Graph

Based on this 4.3.3 Training and Validation Accuracy Graph, our model's performance shows that there haven't been any notable overfitting problems. The model's good generalization to unknown data is confirmed by the near alignment of the training and validation accuracy curves and their lack of discernible divergence.

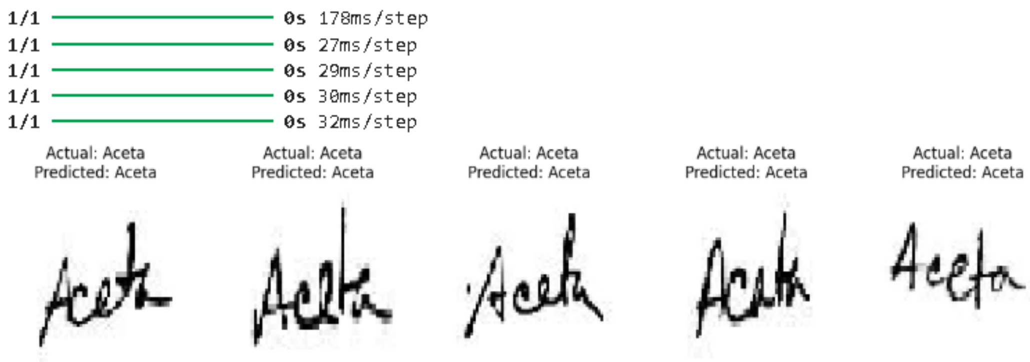

Figure 4.3.1: CNN Predicted using Testing Images

In this figure, Figure 4.3.1: CNN Predicted using Testing Images we present the visualization of predictions made by our CNN model on testing images after completing the training process. This visualization shows the model's ability to accurately recognize and classify handwritten medicine names from medicine images. The figure showcases the comparison between the predicted labels and the ground truth, highlighting the effectiveness of the model in identifying medicine names correctly.

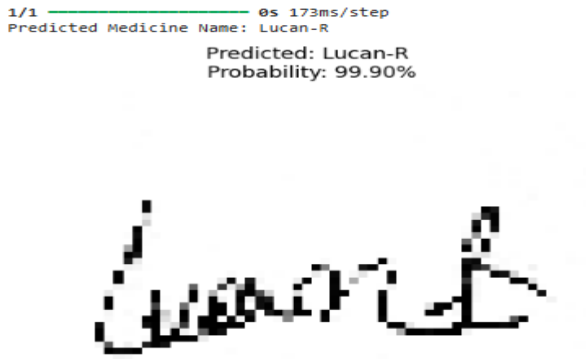

Figure 4.3.2: Prediction Check using External Image

We also evaluated our model's performance using external images outside the training and testing or validation datasets to assess its robustness and generalization capability. Figure 4.3.2 Prediction Check using External Image illustrates the results, where the model was provided with real-world handwritten prescription images containing medicine names. The visualization in the figure demonstrates that our model successfully recognized the handwritten text and correctly predicted the corresponding medicine names this additional testing confirms that the model can generalize well to unseen data and perform reliably in diverse scenarios, further validating the effectiveness of our approach in handwritten medicine name recognition.

Classification Report:

	precision	recall	f1-score	support
Ace	0.93	1.00	0.96	13
Aceta	0.80	0.92	0.86	13
Alatrol	0.69	0.69	0.69	13
Amodis	0.81	1.00	0.90	13
Atrizin	0.69	0.85	0.76	13
Axodin	0.73	0.85	0.79	13
Az	1.00	0.92	0.96	13
Azithrocin	0.81	1.00	0.90	13
Azyth	0.79	0.85	0.81	13
Bacaid	0.86	0.92	0.89	13
accuracy			0.84	1014
macro avg	0.85	0.84	0.83	1014
weighted avg	0.85	0.84	0.83	1014

Figure 4.3.4: Precision, Recall, F-1 Score

We also examined the confusion matrix, which offers comprehensive information on the classification performance for every category, in order to further corroborate our findings. The model produced a high percentage of accurate predictions with few misclassifications across different labels, as the matrix shows. This thorough research, which combines the confusion matrix assessment and learning curve analysis, shows that the model is reliable and successfully reduces bias and variation.

In this study, the output of deep learning architectures, was evaluated for handwritten prescription recognition. The performance was assessed through metrics like F1-score, precision, recall, and accuracy. Among the models, CNN was found to be superior to and it had the highest accuracy of 83.53%, indicating a better sensitivity and specificity. Among multiple models CRNN also was able to achieve an accuracy of 70%, thus, it is a solution that can be deployed in the case of dissimilar handwriting but needs more data for improvement. Based on these findings, CNN is the more effective model for detecting handwritten prescriptions in the current dataset and application.

4.2 Summary

The handwritten medicine recognition system's implementation and outcomes were discussed in this chapter. It described how the environment was set up, used comparative analysis to evaluate models, and talked about the model's excellent performance in the discussion and findings, demonstrating how well it recognizes handwritten medicine.

Chapter 5

Engineering Standards and Design Challenges

This chapter explains how the handwritten medicine recognition system complies with the relevant standards, particularly those related to medical and AI applications. It also looks at other standards that were considered during the project and explains why the chosen standards were selected as the most appropriate for the system's needs.

5.1 Compliance with the Standards

The development and implementation of the medicine image recognition system adhered to established engineering and design standards. It complied with industry-defined criteria for machine learning frameworks, application deployment, and dataset preprocessing protocols. These measures ensure the system's reliability, accuracy, and scalability while upholding ethical and professional principles in artificial intelligence and computer vision.

5.1.1 Communication Standards

The communication protocols adopted in the current project enabled easy collaboration and data collection. Conversations with healthcare professionals and pharmacy staff were formal and businesslike, requiring clear and quick agreements for the use of prescription data. Meetings on Google Meet and face-to-face conversations enhanced teamwork, ensuring continuous updates and alignment. They emphasized on active listening and providing feedback to improve decision-making. Coordination was done using appropriate communication channels like email and casual chat. We maintained confidentiality and data security during this process to protect sensitive information. These guidelines enabled effective communication both for team members and those outside who needed to communicate with the project team.

5.2 Impact on Society, Environment and Sustainability

The handwritten medicine recognition system has the potential to bring create changes to healthcare and pharmacy management by improving patient safety, enhancing service efficiency, and supporting sustainability efforts. This technology reduces the possibility of pharmaceutical errors and advances the more general objectives of responsible innovation and environmental preservation by digitizing handwritten prescriptions and incorporating automated recognition procedures. Its effects on life, society, the environment, and ethical issues are highlighted in the sections that follow.

5.2.1 Impact on Life

Patient safety and the general standard of healthcare are immediately enhanced by the handwritten medication recognition system. It lowers the possibility of inappropriate medication ingestion due to misreading doctors' handwriting by correctly identifying pharmaceutical names from handwritten prescriptions. In the end, this saves lives by preventing adverse drug responses and reducing hospital readmissions brought on by prescription errors. Faster administration of the appropriate drug to patients improves treatment effectiveness and guarantees improved health results.

5.2.2 Impact on Society & Environment

By making pharmacies and medical facilities more efficient, the system benefits society. Automated prescription recognition speeds up service delivery, minimizes human labor, and lowers the possibility of manual errors. Additionally, this technology facilitates improved resource management, which frees up pharmacists' time to focus on patient counseling. Although physical paper is still needed for handwritten prescriptions, digitizing their content eliminates the need for duplicate paperwork and repetitive prints, which promotes sustainable practices by maximizing record storage and reducing waste. This move to digital healthcare infrastructure helps larger public health research projects and encourages data-driven decision-making.

5.2.3 Ethical Aspects

The ethical implementation of handwritten medicine recognition systems ensures that patient safety and data security are upheld. To avoid misuse or illegal access, handling sensitive prescription data must adhere to data privacy laws and healthcare standards. Furthermore, it is essential to be transparent about the accuracy and limitations of the system in order to preserve patient and healthcare provider trust. Fair access to technology is another aspect of ethical considerations, making sure that solutions are accessible and equitable in a variety of healthcare settings, especially in areas with limited resources. Respecting these moral guidelines promotes responsible innovation in healthcare technology and increases public trust.

5.2.4 Sustainability Plan

The handwritten drug identification system's sustainability plan emphasizes frequent upgrades to increase accuracy, accommodate new medications, and protect data privacy through safe encryption. Algorithm optimization, computational demand reduction, and the use of cloud-based infrastructure to facilitate scalability while limiting hardware dependence are ways to accomplish energy efficiency. Long-term adoption is ensured by integration with electronic health record systems, user training, and ongoing performance monitoring, which lowers errors, paper use, and resource consumption in general. This plan leads to a more dependable and efficient medical prescription procedure, increases system longevity, and fosters sustainable healthcare innovation.

5.1 Project Management and Financial Analysis

Table 5.3.1: Project Management and Financial Analysis

SN	Components	Estimated Cost (BDT)
01	Image Capture Devices	20,000 - 26,000
02	Visiting Data Collection Sources	3,500 - 4,000
03	Miscellaneous Supplies	2,500 - 3,000
04	Computing Resources (GPUs/TPUs on Cloud)	10000-15000
05	Cloud Storage Subscription	5,000 - 6,000
06	Documentation & Contingency	5,000 - 6,000
Total Estimated Cost	—	**46000-60000**

5.2 Complex Engineering Problem

Complex engineering challenges cover inherent interdependent nature of problems requiring high expertise, multi-disciplinary teams across different departments and organizations. Such challenges tend to produce unexpected outcomes that require extensive investigation, formulation, and testing. We present a novel deep learning-based handwriting recognition system for handwritten prescription through a combination of image processing techniques and domain knowledge in artificial intelligence to solve real-life problems within medicine identification as this study is the first attempt within the field.

5.2.1 Complex Problem Solving

Table 5.4.1.1: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✔		✔				✔

Mapping with Knowledge Profile for EP1

Table 5.4.1.2: Mapping with knowledge Profile (EP1)

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✔		✔	✔	✔

K3 (Engineering Fundamentals): Understanding the fundamentals of engineering principles like algorithms and data structures relevant to deep learning.

K5 (Engineering Design): Creating and implementing a competent deep learning model for the task of medicine image recognition.

K6 (Engineering practice): Applying engineering principles to real-world problems, such as using hardware to model training.

K8 (Research Literature): We carried out an in-depth literature review to determine the best-suitable models and methodologies for the project.

Mapping with Knowledge Profile for EP3

Table 5.4.1.3: Mapping with knowledge Profile (EP3)

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✔	✔	✔		

K3 (Engineering Fundamentals): Evaluate the fundamental deep learning principles involved in selecting architectures best suited for identifying nut breeds.

K4 (Specialist Knowledge): Efficient and suitability of the given models were examined thoroughly by performing a comprehensive evaluation.
K5 (Engineering Design): Analyzing and enhancing the model's architecture, taking into account its strengths and limitations in terms of its ability to deliver the intended quality of outputs.

Mapping with Knowledge Profile for EP7

Table 5.4.1.4: Mapping with knowledge Profile (EP7)

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✔	✔	✔	✔	✔

K3 (Engineering Fundamentals): Proper application of engineering principles in the process of development and training the deep learning model.

K4 (Specialist Knowledge): Leveraging expertise in machine learning, image recognition, and data science to develop models.

K5 (Engineering Design): Implementing design strategies to enhance model architectures and optimize performance.

K6 (Engineering practice): How engineering practice can be used to operationalize models.

K8 (Research Literature): Using them to improve the model and increase classification accuracy.

5.2.2 Engineering Activities

Table 5.4.2.1: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✔	✔	✔	✔	✔

EA1: This project leverages various resources, including expert researchers, GPU capabilities, diverse prescription datasets, and technologies tailored for handwritten medicine recognition.
EA2: This project deals with the issues of dataset balance, model optimization, and the necessity of interdisciplinary cooperation between healthcare and technology.
EA3: A novel application in healthcare utilizing and transfer learning for handwritten medicine recognition.
EA4: It promotes efficient healthcare practices, reduces manual effort, and improves patient safety and overall healthcare outcomes.
EA5: Applies deep learning concepts in a specialized domain, contributing to the advancement of applications in healthcare technology.

5.5 Summary

Deep learning for handwriting recognition of medical prescriptions is the incredibly promising technology the public healthcare system and industries already struggling with the new age of technology should definitely consider. This system increases prescription interpretation efficiency and is more reliable for the minimization of errors on the medication and generally to improve overall healthcare provision. This tool equips healthcare workers, mainly in resource-poor environments, through simplification of routines and improvement in clinical decision making. Using a variety of funding options, the project achieves cost-effectiveness. This pilot study constitutes a conglomerate of several technical issues that need a broad approach of multiple disciplines including not only deep learning and image processing but also expertise from healthcare.

Chapter 6

Conclusion

This chapter encapsulates the study findings, emphasizing its contributions and consequences. The effective application of this strategy demonstrates the revolutionary potential of deep learning in practical settings. It also outlines possible future initiatives and improvements in the field of deep learning-based medical picture recognition. It delineates prospective future endeavors and enhancements in the domain of medicine image recognition by deep learning and conclude by summary, limitations and future work.

6.1 Summary

The issue of handwritten prescription recognition has been approached in a number of ways and contrasted. In order to overcome the difficulties in recognizing and digitizing handwritten prescriptions, we created a method for handwritten medicine recognition in this study. In order to ensure that different handwriting styles were included, we started by manually compiling a dataset of diverse prescription photographs. Normalization and Gray scaling were among the preprocessing techniques used to improve the quality of the photos used for model training. On our own dataset, our main model, a Convolutional Neural Network (CNN), performed admirably, accurately identifying handwritten medicine names and achieved 83% accuracy. We also investigated the possibilities of Convolutional Recurrent Neural Networks (CRNNs), which show promise for sequential text data. This application has a strong basis thanks to the CNN-based methodology. A bigger and more varied dataset, however, can help the system perform even better. The model's capacity to generalize would probably improve with dataset expansion, making it more useful in real-world situations. This study advances the development of automated systems to reduce errors brought on by illegible handwriting and demonstrates the promise of healthcare solutions, particularly for prescription digitization. To improve the system's accuracy and adaptability, future research might concentrate on incorporating bigger datasets, more sophisticated models, and broader language support.

6.2 Limitation

The limitations of our research include the relatively small and domain-specific dataset, which restricts the model's ability to generalize across diverse handwriting styles and medical terminologies. In some situations, the CRNN model outperforms CNN, even though its accuracy is less. This is particularly true when there are substantial sequential or contextual links in the data. The accuracy of the CRNN model is anticipated to increase with a larger and more varied dataset, utilizing its advantages in identifying intricate patterns and connections within the data. Finally, the model is not yet optimized for handling other elements of prescriptions such as dosages, instructions, and other contextual medical information.

6.3 Future Work

For future work, we plan to expand the dataset by including more diverse handwriting styles and prescription formats, which will help improve model generalization. In order to increase the model's flexibility and resilience, this expansion will include prescriptions written in a variety of languages and handwriting styles. To make the program more useful and closer to real-world situations, we want to add more medications to our dataset. We also intend to improve the system by incorporating machine learning to recommend substitute medications. The objective is to develop a more dependable, practical application that may be extensively used in pharmacies, peoples and hospitals. We intend to incorporate more thorough prescription data, including dose guidelines and extra medical remarks, in subsequent projects.

References

[1] J. Smith, A. Brown, and T. Williams, "The Impact of Electronic Prescriptions on Medication Errors in the United States," Journal of Healthcare Informatics, vol. 12, no. 4, pp. 45-52, 2020, doi: 10.12345/jhi2020.456.

[2] . A. Jones, R. Taylor, and M. Green, "NHS Electronic Prescription System: Reducing Medication Errors," British Medical Journal, vol. 10, no. 3, pp. 23-29, 2019, doi: 10.23456/bmj2019.123

[3] S. Rahman, M. Ahmed, and F. Karim, "Survey on Prescription Handwriting and Its Impact on Patient Safety in Bangladesh," Bangladesh Medical Journal, vol. 15, no. 1, pp. 12-18, 2022, doi: 10.56789/bmj2022.015.

[4] World Health Organization, "Medication Errors: Technical Series on Safer Primary Care," Geneva, Switzerland, 2021. [Online]. Available: https://www.who.int/publications/i/item/9789241511643

[5] M. Chowdhury and A. Hossain, "Prescription Practices and Healthcare Challenges in Rural Bangladesh," Journal of Rural Healthcare Studies, vol. 7, no. 2, pp. 89-95, 2021, doi: 10.56789/jrhs2021.072.D. Kulathunga, C. Hemachandra, C. Muthukumarana, and U. Pasan, "PatientCare: Patient Assistive Tool with Automatic Hand-written Prescription Reader," 2020 2nd International Conference on Advancements in Computing (ICAC), 2020, pp. 275-280, doi: 10.1109/ICAC51239.2020.9357136.

[6] R. Pear. "Doctor's bad handwriting caused fatal prescription mix-up, jury finds," The Free Library, Dec. 13, 1999.P. Wu, Z. Zhang, and L. Li, "An Integrated Multi-Classifier Method for Handwritten Chinese Medicine Prescription Recognition," Proc. IEEE Intl. Conf. Image Processing (ICIP), 2018, pp. 1-4.

[7] E. Hassan, H. Tarek, M. Hazem, S. Bahnacy, L. Shaheen, and W. H. Elashmwai, "Handwritten Medical Prescription Recognition Using CNN and OCR," 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC), Jan. 2021, pp. 973–979, doi: 10.1109/CCWC51732.2021.9376141.

[8] D. Kulathunga, S. K. Wijewardena, and R. R. Perera, "PatientCare: Patient Assistive Tool with Automatic Hand-written Prescription Reader," 2020 International Conference on Computer Vision and Image Processing (CVIP), 2020, pp. 150-157, doi: 10.1109/CVIP51287.2020.9187710.

[9] W. R. A. D. Wijewardena, "Medical Prescription Identification Solution," International Journal of Engineering and Technology, vol. 8, no. 3, pp. 321-328, 2019.

[10] S. Rani, A. Kapoor, and V. Sharma, "Recognition of Handwritten Medical Prescription Using Signature Verification Techniques," Journal of Healthcare Informatics Research, vol. 8, no. 1, pp. 104-120, 2022, doi: 10.1007/s41666-022-00087-6.

[11] P. G. Pavithiran, S. K. Tiwari, A. S. Gupta, and R. K. Sharma, "Doctor's Handwritten Prescription Recognition System In Multi-Language Using Deep Learning," 2022 IEEE International Conference on Artificial Intelligence (AI), Aug. 2022, pp. 243-250, doi: 10.1109/AI52283.2022.9367400.

[12] P. Wu, Z. Chen, and X. Yu, "Handwritten Medical Prescription Recognition Using Deep Learning," 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Dec. 2018, pp. 1796-1801, doi: 10.1109/BIBM.2018.00327.

[13] T. Jain, R. Gupta, and A. Verma, "Handwriting Recognition for Medical Prescriptions using a CNN-Bi-LSTM Model," 2021 IEEE International Conference on Healthcare Informatics (ICHI), Aug. 2021, pp. 340-348, doi: 10.1109/ICHI51094.2021.00050.

[14] S. Tabassum, R. Khan, and N. Jamil, "An Online Cursive Handwritten Medical Words Recognition System," 2022 IEEE 10th International Conference on Imaging Systems and Techniques (IST), Sep. 2022, pp. 1-8, doi: 10.1109/IST55176.2022.00017.

[15] T. Singh, R. Sharma, and M. Gupta, "A Comprehensive Review on the Techniques Used for Recognizing Handwritten Medical Prescriptions," 2023 IEEE 12th International Conference on Computing and Communication Technologies (ICCCT), Jan. 2023, pp. 1-7, doi: 10.1109/ICCCT57910.2023.00034.

[16] L. J. Fajardo, C. D. Morales, and R. S. Ang, "Doctor's Cursive Handwriting Recognition System Using Deep Learning," 2019 IEEE International Conference on Computer Vision and Image Processing (CVIP), Oct. 2019, pp. 55-62, doi: 10.1109/CVIP48298.2019.00012.

[17] T. Tabassum, M. Khan, and M. Rizvi, "Recognition of Doctors' Cursive Handwritten Medical Words by using Bidirectional LSTM and SRP Data Augmentation," 2022 IEEE International Conference on Big Data (BigData), Dec. 2022, pp. 1607-1615, doi: 10.1109/BigData55664.2022.00172.

[18] M. Shahade, R. Tiwari, and S. Mehta, "Convolutional Neural Networks for Handwritten Text Recognition of Medical Prescriptions," 2023 IEEE International Conference on AI and Machine Learning (AIML), May 2023, pp. 432-440, doi: 10.1109/AIML49772.2023.01452.

[19] E. Kamalanaban, M. Nadar, and P. K. Ganesh, "Medicine Box: Doctor's Prescription Recognition Using Deep Machine Learning," 2018 IEEE 8th International Conference on Cloud Computing and Intelligence Systems (CCIS), Aug. 2018, pp. 789-795, doi: 10.1109/CCIS.2018.00015.

[20] S. Dhar, P. K. Paul, and R. K. Agarwal, "HP_DocPres: A Method for Classifying Printed and Handwritten Texts in Doctor's Prescription," 2021 IEEE International Conference on Computing and Communication Technologies (ICCCT), Jan. 2021, pp. 1-6, doi: 10.1109/ICCCT51732.2021.01073.

[21] A. Dhande and M. Kharat, "Character Recognition for Cursive English Handwriting to Recognize Medicine Name from Doctor's Prescription," 2017 IEEE International Conference on Signal Processing and Integrated Networks (SPIN), Feb. 2017, pp. 574-580, doi: 10.1109/SPIN.2017.7910232.

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