

FIT3163 Data Science Project Part 1

Project Proposal & Literature Review
Automated Health Information System

Team MDS2

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Word Count: 15, 200

Date: 25 May 2024

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Automated Health Information System

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1. Introduction

1.1 Project Aim

Our project "Automated Health Information System (AHIS)" is to transform the way healthcare data is managed and accessed by utilizing advanced automated data entry technology. The project team includes Foo Kai Yan as the project manager, Eunice Lee in charge of Quality Assurance (QA), Alicia Quek and Jesse Yow as Technical leads, all working under the supervision of Dr. Muhammad Fermi Pasha. In order to accomplish this goal, a module for recognizing handwritten text will be integrated into a web-based system that smoothly merges with a mobile app, improving efficiency and accuracy in entering data.

The primary goal of AHIS is to develop and implement an advanced health information system that seamlessly integrates features for identifying handwritten data. This system can accurately transcribe both cursive and non-cursive handwriting, ensuring accurate recording of handwritten notes and prescriptions in the patients' database. The objective is to reduce the need for manual data entry techniques and assist medical professionals in their daily data tasks.

One core aspect of our project involves expanding the current web-based health information system to a mobile application platform. This incorporation aims to give healthcare providers the option to input patient information by scanning handwritten notes directly into the system via mobile devices for added flexibility. This function will speed up the data entry process, providing instant access to patient information and improving the overall user experience and satisfaction.

In order to maintain the security and reliability of patient data, the AHIS will include strong access controls to make sure that only approved individuals are able to access the database system. This action is essential to protect patient confidentiality and data integrity by avoiding unauthorized access and changes to patient information.

Furthermore, the project will integrate a database architecture that can efficiently manage the increasing amount of patient data. This scalability is important to meet the growing need for healthcare services and the associated data production.

1.2 Prospective Plans Summary

The project plan for this semester, which has been completed, focused on extensive research and planning for developing a web-based health information system integrated with a Handwritten Text Recognition (HTR) module. Initially, the team conducted preliminary research to understand the project topic, define objectives, scope, and identify potential limitations and risks. Following this, the team spent several weeks studying current health information systems, investigating handwritten recognition tools, and sourcing relevant datasets. Suitable machine learning models were selected, and an integration

strategy was developed. Concurrently, user, functional, and technical requirements were gathered and identified to inform the initial design concept and project architecture.

During the winter break ahead, the team will focus on revisiting previous knowledge and acquiring the necessary skills to complete the project, as the team is inexperienced in this area. This preliminary preparation will improve our abilities for the next semester.

During the upcoming semester, starting in early June and ending in late October, the implementation phase will commence. At first, the team will establish the development environment and set up the necessary software. Afterwards, there will be a lengthy time allocated for both backend and frontend development of the system on the web. The primary focus of backend development will be the establishment of core features and guaranteeing robust and secure data processing and storage within the system. Once the backend is established, the frontend development will be started where the end product is to create a user-friendly interface, ensuring that the system is easy to navigate for users.

After completing the development of the web-based system, the team will integrate the HTR module, ensuring that it works seamlessly with the rest of the system. This integration phase will also include making the system compatible across various platforms to ensure broad usability.

The project will then enter the testing phase. This phase will begin with unit testing to verify that individual components function correctly, followed by integration testing to ensure that the components work together as intended. User acceptance testing will be conducted to validate the system with end-users, ensuring it meets their needs and expectations. During this phase, system performance will be monitored closely to identify and address any issues.

After testing, the team will gather and respond to user feedback by making required changes to enhance the system. Scheduled maintenance will be conducted to guarantee continued dependability and performance, with any discovered bugs or problems being promptly fixed.

In the final weeks of the semester, the team will prepare comprehensive documentation, including user manuals and code documentation. A comprehensive project report will be created to outline the progress and results of the project. The project will conclude with a final presentation at the end of October, where the completed system and its abilities will be demonstrated.

1.3 Anticipated Outcome

Our team aims to self-implement a basic health information system that can maintain all patient records and include all the data entry processes of a clinic, accessible through a website. If time constraints arise, we may use an open-source website as a foundation, modifying it to suit our project, as our main intention is to implement the HTR model. The website will be made mobile accessible.

Users will be able to register patients, schedule appointments between doctors and patients, and allow doctors to record patient diagnoses. The system will enable querying patient data within the website's database. To ensure the security of patient data, features such as user authentication and input validation will be built into the website.

The HTR model will be integrated into the patient registration and diagnosis features, allowing users to upload images of handwritten text, which will automatically populate the corresponding fields. This

functionality aims to significantly reduce the time and effort required for data entry, improving overall efficiency in healthcare data management.

1.4 Report Overview

This report begins by providing an introduction of our project, detailing our objectives, and then explores in more detail the context of our project's subject and a review of literature on similar projects. After this, we will outline our project management strategies, which include the project Overview, Project Scope, Project Organization, Management Process, Monitoring and Controlling Mechanisms, Schedule, and Resource Requirements.

Following the discussion of the project management plan, we will outline the external design of the website and the toolsets used in the methodology section. Following this, there will be a thorough testing plan that will specify our approach for carrying out the testing phase. The report ends with a recap of important points and perspectives.

2. Literature Review

2.1 Background Information & Project Rationale

Health Information Systems (HIS)

The adoption of health information systems throughout the years, allow healthcare facilities to improve patient outcomes by storing health records of patients digitally. This enables medical staff to have instant access to patient data, improving doctor-patients interactions and patient quality care. However, with the use of such a system, healthcare professionals often have less time for direct patient care due to the significant amount of time spent manually inputting patient information in the system. Moreover, some doctors may find it difficult to transition from handwritten prescriptions to digital systems due to their unfamiliarity with the technology used for the system. In addition to being time-consuming, manual data entry may be prone to mistakes due to human error, which can impact patient care negatively.

To solve these problems, our project aims to create a mobile-friendly, web-based AHIS that incorporates artificial intelligence (AI) tools like HTR to simplify and streamline data entry. With the use of this system, medical personnel can accurately and automatically scan handwritten notes, eliminating the need for human input, thus lowering the risk of human error, which in turn, lead to an efficient data entry process.

Optical Character Recognition (OCR)

During the 1970s, optical character recognition (OCR) was developed with the purpose of transforming handwritten content into machine-readable text (IBM, 2024). Currently, OCR is frequently utilized for extracting data from a range of sources including scanned files and images. OCR technology in healthcare enhances big data modeling by transforming scanned documents into PDFs and recognising words and characters from images This specific function is crucial to accelerate the data entry process.

Doctors frequently write prescriptions and documents for patients by hand. Therefore, by incorporating a HTR model, healthcare professionals would benefit significantly from the automatic transformation of handwritten notes to digital records. Hence, OCR would be a crucial component of the HTR model implemented in our AHIS project. Even though integrating HTR into the system may pose difficulties, it is

a worthwhile endeavor that can benefit healthcare professionals and enhance the accuracy and efficiency of patient data management. The use of sophisticated AI technologies like handwriting recognition in our AHIS assists us in achieving our goal of enhancing healthcare delivery.

2.2 Related Research and Existing Work Evaluation

Following 12 research papers that have different or similar approaches on HTR in the healthcare industry, there is a diverse landscape of methodologies and techniques found, aimed at improving the accuracy and efficiency of handwritten recognition systems. Each research paper has an explanation of their approach and techniques used.

AI-backed OCR in Healthcare

The research paper by (Gifu, 2022) provides a comprehensive evaluation of existing OCR systems within the context of healthcare that particularly focuses on handwritten medical documents. The study emphasizes the value of OCR technology in optimizing document processing processes by examining the difficulties involved in manual transcribing and the growing need for automated solutions in healthcare settings. The authors discuss the limitations of traditional OCR systems such as Tesseract and Google Vision in accurately recognizing handwritten text, especially in medical records containing specialized terminology and different writing styles. The research illustrates the potential of AI-driven OCR systems to address these issues and achieve high levels of accuracy in character recognition tasks through a thorough analysis of deep learning-based techniques which are Convolutional Neural Network (CNN) and Convolutional Recurrent Neural Network (CRNN) architectures. Furthermore, the paper evaluates the performance of the proposed OCR models in comparison to existing state-of-the-art (SoTA) systems, highlighting their effectiveness in handling handwritten medical documents and their potential to drive significant improvements in document processing efficiency and accuracy.

Increasing The Accuracy Of Handwriting Text Recognition in Medical Prescriptions With Generative Artificial Intelligence

The research paper by (Yakovchuk & Vasin, 2023) provides a thorough assessment of previous efforts in handwriting text recognition that particularly focuses on medical prescriptions. The authors note the difficulties in identifying handwritten content such as differences in handwriting styles and the use of specific medical language while acknowledging the importance of digitizing medical records for enhancing healthcare services. Traditional OCR systems are discussed in terms of their limitations in accurately deciphering handwritten medical prescriptions. The evaluation underscores the need for tailored approaches to address the unique challenges posed by medical documents. Additionally, the paper discusses the application of deep learning techniques such as recurrent neural networks (NN) and Connectionist Temporal Classification (CTC), in existing systems, highlighting their potential but also emphasizing the necessity of further advancements to achieve higher accuracy rates. Overall, the evaluation sets the groundwork for proposing an improved approach based on generative artificial intelligence to enhance recognition accuracy in medical prescriptions.

An Online Cursive Handwritten Medical Words Recognition System for Busy Doctors In Developing Countries For Ensuring Efficient Healthcare Service Delivery

This research paper by (Tabassum et al., 2022) focuses on the development of an online cursive handwritten medical words recognition system to address the challenges faced by doctors in developing

countries. This research was conducted in Bangladesh where handwritten prescriptions are abundant but often illegible. The research conducted an online survey to understand the current state of handwritten prescription usage in the medical practice of Bangladesh revealing that 97.1% of Bangladeshi doctors still generate handwritten prescriptions. The difficulty of reading these prescriptions often leads to adverse medical consequences such as selecting the wrong medicine, improper dosage which may result in many patients' deaths. The proposed data augmentation technique, Rotate, Shift, and Stretch (RSS) is introduced to expand the dataset and improve recognition efficiency. In evaluating the suggested approach, the paper reports an average accuracy of 93.0% with RSS and Bidirectional LSTM data augmentation which is notably higher than recognition without data enlargement. Furthermore, it is further discussed the potential application of the proposed recognition technology in a smartpen for doctors that aims to reduce medical errors, save costs and ensure healthy living in developing countries. The evaluation also contrasts the proposed method with current datasets and handwriting recognition systems, emphasizing the lack of doctors' handwriting datasets and the necessity for a specialized dataset for identifying doctors' handwriting in Bangladeshi prescriptions.

Optical Character Recognition System in Healthcare and Hospital Management

This research paper by (Patil et al., 2024) involves a comprehensive assessment of the current state of OCR technology in healthcare and hospital management. The evaluation encompasses various aspects including data collection, model training, testing and evaluation, literature survey, Unicode data processing, data mining and feature extraction, model building, and prediction. It emphasizes the importance of data collection in influencing the accuracy and robustness of OCR models particularly in recognizing different paths, transitions and complexities in text. It also highlights the significance of rigorous testing and evaluation that utilizes metrics such as Character Error Rate (CER) and Word Error Rate (WER) to quantify accuracy and effectiveness. Additionally, the literature survey explores machine learning approaches and deep learning techniques for recognizing handwritten medical terms. This showcases the potential for improving digital prescription systems. Besides that, the authors also address the post-processing phase related to Unicode data processing that emphasizes the importance of refining the OCR system's output and ensuring compatibility with Unicode character units. Furthermore, it discusses the essential role of data mining in extracting relevant features from preprocessed images of handwritten text that impacts the model's ability to learn and understand text accurately. The evaluation also delves into the model building and prediction phase that highlights the use of neural network architectures and advanced algorithms to accurately recognize handwritten text and enhance productivity in healthcare settings.

MediCrypt: Survey on Automated Recognition of Handwritten Medical Prescriptions for Enhanced Healthcare Efficiency

This research paper by (Nimbalkar et al., 2024) provides a comprehensive assessment of the pros and cons of techniques used in the development of recognition systems for handwritten medical prescriptions. It highlights the successful application of advanced neural network models such as artificial neural networks (ANN), CRNN and deep learning techniques in recognizing and interpreting handwritten prescriptions. It emphasizes the importance of clear handwriting for accurate recognition and the potential challenges posed by illegible or complex prescriptions. Additionally, the evaluation addresses the need for ongoing optimization and updates to ensure consistent and reliable performance of recognition systems. Furthermore, it discusses the potential future directions for development and

expansion including integration with electronic health record systems, support for multiple languages and collaboration with healthcare providers and regulatory bodies to refine the system's compliance with standards and regulations. The author also states that this research paper provides valuable insights for researchers seeking to devise more accurate and error-reducing methods for automated recognition of handwritten medical prescriptions.

Interpreting Doctor Notes using Handwriting Recognition

This research paper by (Sable et al., 2024) highlights the challenges associated with interpreting handwritten medical prescriptions and the potential for machine learning and deep learning techniques to address these challenges. It discusses the use of CNNs and RNNs for recognizing and translating handwritten medicine names from prescription notes. It also emphasizes the importance of data preprocessing techniques such as image subtraction and noise reduction, to improve the quality of images before applying machine learning algorithms. Additionally, the research paper presents the proposed system's aim to address the problem of doctors' difficult-to-read handwriting which can lead to misunderstandings and errors when filling prescriptions. The system is designed as a mobile application that allows users to upload images of prescription notes which are then pre-processed and analyzed using deep learning techniques. The proposed approach involves the development of a dataset of handwritten medical terms and the use of data augmentation techniques to improve recognition efficiency and accuracy. Lastly, it also discusses the potential of using machine learning techniques to recognize and translate handwritten prescription notes written in various languages and the development of a mobile application for this purpose.

Towards an On-line Handwriting Recognition Interface for Health Service Providers using Electronic Medical Records

This research paper by (Cruz et al., 2020) focuses on the development and testing of an online handwriting recognition interface for health service providers using electronic medical records (EMRs) in the Philippines. The study presents a comprehensive analysis of the challenges associated with EMRs such as poor usability hindering physician-patient interaction and causing stress. It proposes a solution in the form of a user-friendly handwriting recognition interface to facilitate data entry in EMRs that aims to improve usability and decrease physician time spent on documentation. The prototype created uses open-source technologies and hardware-agnosticism to facilitate low-cost deployment of the handwriting recognition interface. Additionally, the use of the MyScriptJS graphic library which employs machine learning algorithms for handwriting recognition. The prototype was tested with medical students and health service providers, demonstrating a handwriting recognition accuracy of 34% and 42%, respectively. The findings also revealed challenges with specialized words and accidental markings affecting recognition accuracy that paves the way for future enhancements through ontology, machine learning and AI.

Development of an optical character recognition pipeline for handwritten form fields from an electronic health record

This research paper by (Rasmussen et al., 2011) shows the development and preliminary evaluation of an OCR pipeline for extracting data from handwritten medical records. The study leverages existing third-party OCR engines and presents a modular pipeline approach that allows for flexibility and customization. The specific task was to identify cataract type and severity using purely automated

methods for a genome-wide association study. The study cohort consisted of a subset of 949 ophthalmology forms and the pipeline was tested with multiple configurations of OCR engines. The results showed that the optimal configuration, using the Nuance and LEADTOOLS engines in parallel, achieved a positive predictive value of 94.6% and a sensitivity of 13.5%. The study also highlights the limitations such as the focus on a specific disease, the use of a limited vocabulary and emphasizes the feasibility and potential applicability of integrating multiple inexpensive OCR engines in a modular pipeline.

Optimization of a Handwriting Recognition Algorithm for a Mobile Enterprise Health Information System on the Basis of Real-Life Usability Research

The research paper by (Holzinger et al., 2012) delves into the application of machine learning techniques specifically Hidden Markov Modeling (HMM) and NN to optimize the handwriting recognition algorithm for a mobile enterprise health information system. The study emphasizes the use of HMM for pattern recognition tasks that highlights its clear and reliable statistical framework and the efficient algorithms for parameter estimation and model evaluation. Besides that, the research aims to enhance the performance of available handwriting recognition by improving accuracy and error correction. This addresses the challenges of handwriting recognition in real-life environments. The study also underscores the significance of user acceptance and usability in the health care domain as well as the preference for virtual keyboard input over handwriting recognition among participants with higher computer usage. Furthermore, the paper discusses the need for a usable front-end for handwriting recognition like in ambulances and the potential for future developments to focus on data acquisition based on intelligent and comfortable virtual keyboards.

Recognition of Handwritten Medical Prescription Using Signature Verification Techniques

The research paper by (Rani et al., 2022) encompasses a wide range of techniques used for signature verification and medical prescription recognition. These techniques include online and offline verification approaches, handwritten signature verification, Chinese character recognition techniques, Discrete Cosine Transformed (DCT) and sparse representation techniques and a two-stage classification approach combining generative and discriminative modeling principles for online handwritten character recognition. Furthermore, it discusses the use of NN for signature verification, automatic signature recognition approaches using Gabor filter techniques and the use of different classifiers such as Naive Bayes, SVM, gradient boosted, and decision tree for experimental evaluation. The proposed system also involves the use of tablet and stylus for data acquisition, feature extraction and classification model implementation. Besides that, it highlights the use of OCR technology for scanning medicine names and converting them into digital scripts. These techniques collectively contribute to the development of a comprehensive system for medical prescription recognition using signature verification methods.

Building Structured Personal Health Records from Photographs of Printed Medical Records

The research paper by (Li et al., 2015) focuses on assessing the performance of the proposed approach for extracting structured personal health records (PHRs) from printed medical records. It encompasses various techniques that include image processing, OCR and annotation algorithms. The evaluation of post-processing approaches involved the word resegmentation algorithm and multi-engine synthesis algorithm which significantly improved the precision and recall of the system. Additionally, document type annotation algorithms such as keyword-based and Naïve Bayes were evaluated for classification

accuracy. This combination of these algorithms achieved perfect results. Besides that, the evaluation of term matching approaches included exact matching and fuzzy matching algorithms with the combined unigram and bigram approach demonstrating higher precision. This also considered the influence of confidence thresholds on precision and recall as well as the impact of image quality on OCR and annotation performance. The evaluation identified limitations such as errors caused by image defects, OCR engines, and annotation algorithms and suggested potential improvements in image pre-processing, OCR engine synthesis and annotation algorithms to mitigate extraction errors.

A Machine Learning-based Approach to Vietnamese Handwritten Medical Record Recognition

The research paper by (Phung et al., 2022) shows a comprehensive review of related works in the field of text recognition that particularly focus on the automatic transcription of handwritten documents which is a subset of OCR. The paper discusses the evolution of traditional HTR methods which were based on hand-crafted feature engineering and the shift towards Deep Learning as a successful supervised learning framework for large-scale OCR problems since 2015. The authors also provide an overview of the common pipeline for character recognition that includes pre-processing, text localization, text segmentation, and text recognition. Additionally, it evaluates various techniques such as binarization, text localization, and segmentation as well as the use of deep learning architectures, including ResNet, BiLSTM and CTC to convert images into text. The evaluation also includes the discussion of post-processing techniques for error detection and correction in the recognized output. Furthermore, the paper highlights the challenges and limitations of existing methods such as the need for complex language models, character separation, and the requirement for a dictionary. The authors also acknowledge the need for a new post-processing method specifically tailored for medical records due to the unique characteristics of the Vietnamese language and grammar.

2.3 Existing Work Comparison and SWOT analysis

■ MDS2 - SWOT Analysis

In this section, we conduct a comprehensive comparison of existing works related to our project domain, examining their features, approaches used, and their strengths and weaknesses.

AI-backed OCR in Healthcare

Functionality:

The research aims to develop an OCR application for offline character recognition using a combination of RNN and CNN. It focuses on recognizing handwritten characters and converting them into digital text. The project addresses issues in the medical sector such as dispersed datasets, weak consistency, low electronic integration and poor visualization. This inspires the need to improve the digitization of medical records.

Methodologies:

- Employs deep learning approaches, such as CNN and CRNN, to recognize handwritten characters and convert them into digital printed texts.
- Combination of RNN and CNN for offline character recognition to achieve accurate character recognition in the medical field.

• CNN and CRNN demonstrated promising results achieving an average accuracy of around 80% with CRNN showing a slight advantage over CNN.

Strengths:

- Useful for identifying and classifying digital text into editable formats in the Romanian medical field.
- Able to streamline medical records scanning processes and enhance the doctor-patient relationship.
- NLP techniques and deep learning approaches for character recognition in the medical field lead to improvements in accuracy.

Weaknesses:

- Challenges with recognizing all handwritten characters in the Romanian language.
- Lack of data leads to disappointing results.
- Need for further improvement in accuracy and dataset diversity.
- Challenges with dispersed datasets, weak consistency, low electronic degree and low visualization degree in medical care.

Opportunities:

- Adoption for English languages and contribute to the healthcare system globally by expanding the dataset and enhancing the model.
- Integration with the existing EHR Systems improves the overall efficiency of the healthcare data entry processes.

Threats:

• Specific linguistic nuances of Romanian handwriting may present additional challenges that need to be addressed to ensure comprehensive recognition capabilities.

Increasing The Accuracy Of Handwriting Text Recognition in Medical Prescriptions With Generative Artificial Intelligence

Functionality:

The research aims to develop a system for recognizing handwritten text in medical prescriptions by utilizing a handwriting recognition module and post-processing modules to enhance accuracy. It incorporates a generative neural network to analyze and correct recognition errors thereby improving text recognition accuracy. The study evaluates the system's performance with various configurations and requests to the generative network that showcases the potential of generative AI to significantly boost recognition accuracy.

Methodologies:

- Uses handwriting recognition module: the Handprint recognition system which comprises services like Amazon-Rekognition, Amazon-Textract, Google, and Microsoft.
- Post-processing modules for merging words into lines and blocks, taking into account the structure and format of the prescription, and a module for the correction of recognition errors using generative AI.

• Uses an in-house dataset of 40 images of handwritten prescriptions in English to evaluate the accuracy of the system.

Strengths:

- Recognizes handwritten text in medical prescriptions with diverse calligraphy styles and the specificity of medical terminology.
- Use of generative AI in post-processing recognition results demonstrates an improvement in recognition accuracy.

Weaknesses:

- Limited by the specificity of medical terminology which reduces the effectiveness of using common language models and auto-correction.
- Bad at handling complex handwriting, unusual writing styles, and overlapping text during handwriting.
- Limitations of generative AI in correcting grammatical errors.

Opportunities:

- Research in generative AI focus on personalized information selection for medical prescriptions can be further explored.
- Potential to create specialized generative networks tailored to specific user needs, such as identifying essential information about drugs and their dosages. This could enhance the accuracy and relevance of recognition results.
- Combining genetic algorithms with neural networks offers promising possibilities for optimizing the parameters, architecture and weights of these networks, potentially leading to advancements in various fields and tasks.

Threats:

- Effectiveness of generative AI depends on the quantity and quality of training data.
- Generative AI has limitations in recognizing medical terminology in prescriptions.
- The complexity and specificity of medical terms can hinder the effectiveness of common language models and auto-correction potentially impacting the accuracy and reliability of recognition systems.

An Online Cursive Handwritten Medical Words Recognition System for Busy Doctors In Developing Countries For Ensuring Efficient Healthcare Service Delivery

Functionality:

The research paper proposes a machine learning approach to recognize doctors' cursive handwriting and convert it into digital prescriptions. It introduces a novel data augmentation technique, Rotate, Shift, and Stretch (RSS) to enhance the variety of handwriting styles. The study aims to implement this recognition methodology in a smartpen for doctors that enables real-time digitization of prescriptions.

Methodologies:

• Creation of a 'Handwritten Medical Term Corpus' dataset containing 17,431 samples of 480 medical terms.

- Uses Bidirectional Long Short-Term Memory (LSTM) network for recognition that achieves an average accuracy of 93.0%.
- Data augmentation technique, RSS of the handwritten characters to create new augmented data in different forms.

Strengths:

- Efficient healthcare service delivery in developing countries.
- RSS data augmentation technique significantly expands the dataset which improves the recognition accuracy of doctors' cursive handwriting.
- Smartpen has the potential to reduce medical errors, save costs and ensure efficient healthcare service delivery.

Weaknesses:

- Further improvement to ensure reliable and consistent performance.
- Relies on a relatively small dataset.
- Smartpen application is still in the concept stage.

Opportunities:

• Technique can be applied to other industries such as education, where tools like smartpens can be used to digitize handwritten notes, providing similar benefits.

Threats:

- The extensive data collection required for the system raises concerns about privacy and data security.
- Healthcare professionals may have difficulties in adopting new technologies which could require extensive training and adaptation periods.

Optical Character Recognition System in Healthcare and Hospital Management

Functionality:

The OCR system is designed to accurately extract text from digital images by integrating advanced machine learning and deep learning techniques to enhance recognition accuracy and efficiency. It features Text-to-Speech functionality to improve accessibility for visually impaired users and employs Unicode Approximation Models (UAMs) for precise character recognition and smooth integration with existing text processing systems.

Methodologies:

- Data collection, image preprocessing, model training, data mining, feature extraction, classification, and post-processing.
- Uses CNNs, RNNs and LSTMs for model building and training.
- Integrates NLP in the post-processing stage to enhance text output and utilizes Unicode data processing to ensure correct character recognition.
- The OCR model is validated using additional tools to ensure accuracy and reliability.

Strengths:

- Able to handle various handwriting styles with high accuracy.
- Unicode data ensures accurate character recognition and seamless integration with existing text processing systems.
- High accuracy and efficiency in text recognition due to the combination of machine learning and deep learning techniques.

Weaknesses:

- Higher complexity in handling diverse languages and scripts.
- Requires significant computational resources and expertise for implementation and maintenance.
- Post-processing stage may introduce additional complexity and potential challenges in optimizing text output.

Opportunities:

- Automating handwritten medical document recognition using OCR improves healthcare delivery allowing healthcare workers to focus more on patient care.
- OCR technology can significantly enhance telemedicine services as patient records are easily accessible during remote consultations.

Threats:

- OCR struggles with poor handwriting or unconventional styles leading to potential data entry errors.
- The digitization of medical records increases the risk of data breaches as electronic records can be more easily disseminated.

MediCrypt: Survey on Automated Recognition of Handwritten Medical Prescriptions for Enhanced Healthcare Efficiency

Functionality:

The research paper revolves around implementing technology to accurately interpret varied handwriting styles prevalent in medical prescriptions. It uses information extraction techniques to identify and extract essential details like medication names, dosages, frequencies, patient information and doctor instructions. Furthermore, quality enhancement methods are utilized to improve image clarity by addressing hardware limitations and suggesting high-resolution image capture techniques.

Methodologies:

- Handwriting recognition technology is implemented to accurately interpret diverse handwriting styles commonly found in medical prescriptions.
- Information extraction techniques are used to identify and extract critical information such as medication names, dosages, frequencies, patient details, and doctor instructions.
- Quality enhancement methods are used to ensure the clarity and quality of input images by recommending high-resolution image capture methods.

Strengths:

- High accuracy rates ranging from 89.5% to 95-98%.
- Enhances patient understanding and overcome language barriers.

Weaknesses:

- Relies on clear handwriting to extract necessary information accurately.
- Dealing with prescriptions in languages outside of its training scope.
- Bad image quality influences the model's performance.

Opportunities:

• The high accuracy and ability to overcome language barriers greatly benefit the healthcare industry improving efficiency in patient administration and meeting high market demand for this technology.

Threats:

• High-resolution capture techniques and the use of better cameras with proper lighting conditions are needed as poor images can reduce text extraction accuracy.

Interpreting Doctor Notes using Handwriting Recognition

Functionality:

The proposed system aims to recognize and interpret handwritten medicine names from prescription notes through the application of deep learning techniques like CNN and RNN. It employs a combination of image processing, machine learning and deep learning methods to enhance medication identification accuracy and minimize errors. The system enhances the overall efficiency and dependability of medicine detection and interpretation by utilizing word segmentation, Unicode, and OCR to facilitate cross-language word matching and maximize pharmaceutical database findings.

Methodologies:

- Converting images using digital technologies and functions to output a magnified image.
- Utilizing algorithms to find patterns and interdependencies in large datasets for accurate outputs and predictions.
- Involving CNN and RNN for image classification and recognition of handwritten characters.

Strengths:

- Improved accuracy of prescription identification using CNN and RNN.
- Recognition and translation of handwritten medicine names accurately.

Weaknesses:

- CNN model limitations: overfitting and performance degradation over time.
- Reliance on image quality and perspective for accurate recognition.
- Increased complexity due to the need of data augmentation and preprocessing techniques

Opportunities:

 Collaboration with pharmaceutical companies could provide access to real-time updates on medication databases.

Threats:

- Risk of overfitting in CNN models may affect the accuracy and reliability of prescription identification as biased prescriptions may exist.
- Variations in the quality of handwritten prescription notes, such as smudges, fading ink, or illegible writing, could result in misinterpretation of the medicine recognition.

Towards an On-line Handwriting Recognition Interface for Health Service Providers using Electronic Medical Records

Functionality:

The research paper centers on developing and testing an online handwriting recognition interface used for health service providers utilizing electronic medical records (EMRs) in the Philippines. The interface captures physicians' handwriting in real-time and swiftly converts it into plain text from handwritten notes to digitized text without interrupting the natural workflow. Following testing by diverse health practitioners, results were reported and future enhancements were proposed to further enhance the interface's functionality, practicality, and user experience.

Methodologies:

- Involves processes such as symbol classification, segmentation and linguistic-based analysis to improve the accuracy of recognition results.
- Integrating medical ontologies for word suggestions, comparing recognition to a local best approximation for word correction and clinical text extraction using cTAKES.
- Integration the SHINEOS+ EMR service within an EMR system aiming to provide a seamless interface in doctor-patient interaction.

Strengths:

- Improved handwriting recognition interface for physician workflow and patient care.
- Low cost deployment of the handwriting recognition interface due to open-source technologies.

Weaknesses:

- Accuracy in recognizing handwritten input was reported at 34% and 42% for medical students and health service providers.
- Specialized words and accidental markings affecting recognition accuracy.
- Challenges in recognizing certain symbols, abbreviations and less defined numbers in medical prescriptions.

Opportunities:

• Exploring advanced machine learning and AI algorithms that can adapt to different handwriting styles, resulting in better recognition results.

Threats:

 Detailed testing and validation of the recognition interface in actual healthcare environments are necessary. Real-world situations bring in complexity that preliminary testing might not fully reflect.

Development of an optical character recognition pipeline for handwritten form fields from an electronic health record

Functionality:

The research centers on the design of forms built for capturing hand-printed data specifically optimized for OCR processing that enables efficient data collection and character segmentation. It outlines the creation of an OCR pipeline for handwritten form fields extracted from electronic health records, utilizing both third-party OCR engines and a customizable modular system. Through experimentation, the pipeline was configured to run various setups, with the most effective combination employing Nuance and LEADTOOLS engines concurrently, achieving a positive predictive value of 94.6% and a sensitivity of 13.5%.

Methodologies:

- The OCR pipeline involves preprocessing, OCR engine processing and postprocessing stages to improve recognition rates and extract data from handwritten forms.
- The use of three OCR engines: the Tesseract OCR engine, the LEADTOOLS Intelligent Character Recognition (ICR) Module and the OmniPage Capture SDK from Nuance Communications.

Strengths:

- The feasibility of integrating multiple and inexpensive general-purpose third-party OCR engines in a modular pipeline.
- Rapid testing of multiple configurations and the logical combination of results from multiple engines to achieve the best performance.

Weaknesses:

- Relatively inexpensive OCR components, and time and resource constraints prohibited an exhaustive comparison of all possible OCR options.
- System was only evaluated on documents created at one institution that focused on one specific disease using a very limited vocabulary.
- Detection rates were low compared with other studies applying OCR techniques on handwritten form fields.

Opportunities:

- Healthcare industry can benefit from the rapid interchange of experimental modules, OCR engines, or cleanup steps within the pipeline. This flexibility allows for adjustments and improvements based on emerging technologies.
- Similar approaches can be explored to enhance their own OCR strategies. The ability to test various configurations and adapt to changing technologies is valuable.

Threats:

• The study intentionally focused on open-source or relatively inexpensive OCR components. However, this narrow scope may limit the applicability of results to other settings or document types. Broader adoption across different domains or institutions could be challenging.

• While using multiple inexpensive general-purpose OCR engines provides flexibility, it may compromise accuracy and feasibility, especially in real-world clinical contexts. Inaccuracies in data extraction and interpretation could affect the reliability of the OCR pipeline.

Optimization of a Handwriting Recognition Algorithm for a Mobile Enterprise Health Information System on the Basis of Real-Life Usability Research

Functionality:

The study aimed to enhance the handwriting recognition algorithm to optimize data acquisition in mobile healthcare specifically in emergency medical care settings. It sought to improve accuracy and efficiency to enhance patient care in practical scenarios. The research emphasized the necessity for a user-friendly interface for handwriting recognition particularly in ambulances and underscored the complexities of recognizing handwritten characters across diverse contexts.

Methodologies:

- Uses Hidden Markov Modeling (HMM) and NN to optimize the handwriting recognition algorithm.
- Involved real-life usability research including participants from the ambulance service, to measure the accuracy and speed of text input using virtual keyboards and handwriting recognition.
- Utilized solid usability engineering methods to improve accuracy and error correction in the handwriting recognition algorithm.

Strengths:

- Usability of different input methods in the context of emergency medical care.
- Potential of HMM and NN to improve handwriting recognition in mobile health care systems.
- Potential for future developments to focus on data acquisition based on intelligent and comfortable virtual keyboards.

Weaknesses:

- Easier to input text with the virtual keyboard than with handwriting recognition.
- The need for further tweaking in recognition accuracy and user acceptance in the health care domain.
- Preference for virtual keyboard input over handwriting recognition among participants with higher computer usage.

Opportunities:

- Handwriting recognition systems can significantly improve data entry efficiency in medical contexts. Fast and accurate input enhances patient care and overall workflow.
- Advancements in machine learning and AI offer opportunities to enhance handwriting recognition algorithms further. system performance has improved incorporating newer techniques.
- Developing effective handwriting recognition systems opens new markets within the healthcare industry.

Threats:

• The field of handwriting recognition is highly competitive. It is essential to keeping pace with technological advancements and innovations

• There might be resistance from users, especially those who always stick to traditional methods. Ensuring high levels of accuracy and usability is critical to overcoming this resistance.

Recognition of Handwritten Medical Prescription Using Signature Verification Techniques

Functionality:

The proposed system aims to create an online handwritten medical prescription recognition system that enables doctors to write prescriptions digitally on a tablet using a stylus while automatically identifying prescribed medicines. It employs signature verification techniques to mitigate the risk of pharmacists misinterpreting medicine names. The system enhances recognition accuracy by storing various features such as pen coordinates, time stamps, and pen-up and pen-down actions during the writing process.

Methodologies:

- Data acquisition using a mobile/tablet and feature extraction using pen-up and pen-down movements.
- Data processing involves preprocessing to remove unwanted data and adding missing values.
- Uses various classification models: Naive Bayes, SVM, gradient boosted and decision tree.

Strengths:

- Uses signature verification techniques to enhance recognition accuracy and prevent potential risks associated with misinterpretation of medicine names.
- Stores different features to significantly enhance recognition accuracy

Weaknesses:

- Require further optimization and feature extraction to improve recognition accuracy.
- Difficulty in handling a wide range of handwritten styles and variations in medical prescriptions.
- Depends on the quality of the handwritten prescriptions.

Opportunities:

- The system enables doctors to record prescriptions on a tablet using a stylus, capturing pen coordinates, time, and pen movements. This technology has the potential to be used in different healthcare environments as well as in other fields requiring handwriting recognition.
- The system improves the accuracy of recognition by adding new characteristics and employing an SVM classifier, which, with appropriate additional research and development done, the method could be further enhanced and improved.

Threats:

- The appearance of text of handwritten prescriptions may vary significantly among various doctors and even the same doctor at different times. This variability may present a difficulty for the system in accurately identifying prescriptions.
- Due to system requirements, doctors are required to use a stylus to write prescriptions on a tablet. This might be difficult to implement as the doctors might be used to writing out prescriptions by hand physically on paper.

Building Structured Personal Health Records from Photographs of Printed Medical Records

Functionality:

This proposed approach integrates OCR with annotation algorithms to extract text from photographed medical records and identify document types, relevant entities and their correlations. It is then used to construct structured personal health record (PHR) documents. Its primary goal is to precisely extract entities like diagnosis names, medication details and test results from medical record photographs which entails efficient organization of patient health information.

Methodologies:

- Image pre-processing algorithms: denoising, binarization, and deskewing, are performed to reduce the influence of low image quality of photographs shot by mobile phones.
- Multiple OCR engines are applied to recognize text and the results of the engines are synthesized to achieve higher performance in recognizing characters of a complex character set.
- Flexible annotation algorithm: fuzzy term matching and regular expression matching are used to locate and identify the entities of interest and a slot-based correlation annotation algorithm is used to locate the related entities.

Strengths:

- Demonstrates effectiveness and applicability in building structured PHRs from real-world prescriptions and lab test reports with high precision and sensitivity.
- System pipeline and sample data flow show a practical and industrial-strength solution for building structured PHRs from printed medical records.
- Wide applicability and potential for adaptation to other languages or hand-written medical records by extending the OCR and annotation modules.

Weaknesses:

- Image quality of photographed medical records significantly affects the performance of OCR and annotation leading to extraction errors.
- Limitation of the OCR engines caused more than half of the extraction errors.
- The system's tolerance to uneven light and shade, Gaussian noise, and skewing in images is not perfect.

Opportunities:

- The system can handle variations in light, shade, noise, and skewing in images may not be perfect but it might be suitable to be used on photos taken by various users with different phones. This flexibility allows for a wide range of uses and implementations.
- Resegmentation and multi-engine synthesis algorithms used in the post-processing methods might improve the precision and recall of the system.

Threats:

• Image defects that are not eliminated would lead to extraction errors which could potentially compromise the system's accuracy and reliability.

• Older or lower quality medical records might be taken in low clarity which might result in some extremely thin strokes disappearing within the images after binarization has been done. System accuracy might be affected.

A Machine Learning-based Approach to Vietnamese Handwritten Medical Record Recognition

Functionality:

The proposed solution is an end-to-end document-digitization system designed for recognizing handwritten medical records in Vietnamese. It employs segmentation at the word-level and utilizes a deep learning architecture comprising ResNet, BiLSTM, and CTC to convert images into text. The primary objectives include accelerating the digitization process of medical health records and creating a digital medical-note dataset for potential medical machine-learning applications.

Methodologies:

- Pre-processing techniques such as binarization, text localization, and text segmentation.
- Deep learning architectures such as ResNet, BiLSTM, and CTC.
- Post-processing techniques for error detection and correction in the recognized output.
- Combination of character-based, word-based and sequence-based methods for text recognition with a focus on word-based classification for Vietnamese text.

Strengths:

- Ability to effectively recognize words with a massive number of labels.
- Not requiring segmentation at the character level.
- Ability to process long strings.

Weaknesses:

- The necessity of a complex language model.
- Heavy dependence on character separation and requires a dictionary.
- Text written outside of the detected writing area when the text overflows to the next column.
- Long arbitrary sequence degeneracy.

Opportunities:

- The HTR method may be applied to more than just Vietnamese handwritten medical records. It could potentially be applied to different languages or medical situations.
- Possible partnership with specialists in fields like natural language processing, computer vision, and healthcare informatics.

Threats:

- The proposed approach may be outperformed by other existing HTR methods.
- Increasing regulations around data privacy could limit access to the diverse datasets needed for training and testing.
- Limited access to computational resources could hinder the ability to process large datasets to further improve the model.
- The proposed system might not integrate well with existing healthcare systems.

2.4 Proposed Project Justifications

The comparative analysis of existing solutions in the healthcare sector underscores the necessity for further advancements in handwritten text recognition and digitization of medical records. Several key points justify the proposed project. Existing solutions such as those employing deep learning architecture like CNNs and RNNs for character recognition show promising but limited accuracy due to challenges in recognizing diverse and complex handwritten characters. This highlights the need for enhanced methodologies that can improve accuracy and handle a wider variety of handwriting styles. Additionally, many existing systems suffer from limited and non-diverse datasets leading to average performance. For instance, the study by (Yakovchuk & Vasin, 2023) using generative AI utilizes an in-house dataset of only 40 images resulted in limitations when dealing with complex handwriting and unusual styles. This indicates the need for larger and more comprehensive datasets to improve recognition robustness.

Besides that, projects like the online cursive handwritten medical words recognition system show high accuracy (93.0%) using data augmentation techniques, yet their practical applications such as the smartpen remain in conceptual stages. There is a clear gap in implementing these technologies in real-world settings to streamline medical workflows and improve healthcare delivery. OCR systems often struggle with multilingual and multiscript recognition. For example, the OCR system in healthcare and hospital management faces higher complexity in handling diverse languages and scripts requiring significant computational resources and expertise. This necessitates the development of more adaptable and efficient OCR solutions capable of handling multilingual medical records .

Furthermore, post-processing methods such as those using generative AI, complex pipelines and other techniques to correct recognition errors demonstrate improvements in accuracy. However, challenges remain in handling complex handwriting, unusual writing styles and overlapping text during handwriting recognition. Real-time applications like the proposed online handwriting recognition interface for health service providers exhibit lower accuracy (34% to 42%) when tested by medical professionals (Cruz et al., 2020). This indicates the need for more robust systems that can maintain high accuracy without interrupting the natural workflow.

2.5 Conclusion

Although handwritten text recognition in healthcare has advanced significantly in recent years, there is still much space for improvement. Creating algorithms that are computationally efficient, generate accurate, high-quality digital text and can withstand the wide variety of handwriting styles and languages included in medical records is a major challenge. Deep learning and hybrid methodologies are promising areas of research for handwritten text recognition as they have the potential to learn and generalize complex patterns in medical handwriting. For instance, the use of CNNs, RNNs, and advanced data augmentation techniques has shown notable improvements in accuracy, yet the need for more comprehensive and diverse datasets persists. Additionally, there is an opportunity to develop handwritten text recognition algorithms tailored to specific applications within healthcare such as electronic medical records (EMRs), prescription digitization and real-time note-taking in clinical settings.

Moreover, emphasizing the importance of interdisciplinary collaboration and stakeholder engagement in driving the development and adoption of these technologies is crucial. Engaging medical professionals, researchers, technologists, and policymakers in the design and implementation process can ensure that the resulting solutions are not only accurate and efficient but also aligned with the needs and workflows

of healthcare providers. Besides that, addressing the scalability and sustainability of the proposed solutions is essential. As healthcare systems continue to evolve and face increasing demands, developing technologies that can scale across different settings and adapt to changing requirements over time is required. Additionally, considering the ethical and privacy implications of digitizing medical records and ensuring compliance with regulatory standards should be integrated into the development process from the outset.

Overall, the field of handwritten text recognition in healthcare is active and expanding with significant potential for further research and development. It is likely that we will see substantial advancements in the accuracy, efficiency and practical applications of these algorithms in the coming years ultimately leading to enhanced healthcare delivery and improved patient outcomes.

3. Project Management Plan

3.1 Project Overview

Our focus is centered on developing an AHIS where the main objective is to transform how healthcare data is managed and accessed. An online platform will be created, along with a mobile app, to streamline the data entry process. One important aspect is the inclusion of a HTR model within the system, making it quicker to convert handwritten medical notes and prescriptions into digital records stored within the database. This new technology aims to speed up the process of entering data, enhance the user experience for healthcare workers, and increase efficiency of the healthcare industry patient administration as a whole. The expected result is an improvement in the quality of patient care, benefiting medical staff and patients alike.

3.2 Project Scope

3.2.1 Project and Product Deliverables

3.2.1.1 Project Deliverables

Milestone 1: Project Initiation Phase

Project objectives, requirements, and scope is defined with the following project deliverables:

- Business Case Study Report
- Mind-map and Project Management Plan Report

Milestone 2: Project Research and Planning Phase

Comprehensive research is done on the project and is defined in the following project deliverables:

- Project Scope Statement, Stakeholder Acknowledgement
- Gantt Chart, Work Breakdown Structure (WBS)
- Requirement Traceability Matrix (RTM), Risk Register
- Team Communication Matrix (Communication Plan)
- Stakeholder Communication Matrix
- Project Concept and Design Report
- Data Analysis Report
- System Design Representation

• Project Proposal and Literature Review Report

Milestone 3: Project Execution Phase

The development of the HTR model, along with the frontend and backend aspects of the project, will be initiated and carried out in alignment with the scheduled timeline. The HTR will be integrated to the AHIS and optimized to improve precision and accuracy during this phase. Project Status reports will be the only project deliverable to be delivered in this milestone.

Milestone 4: Project Testing Phase

Various testing will be performed in accordance with the contents in Chapter 6 of this report. AHIS and HTR will be improved in accordance with the feedback received.

Milestone 5: Project Documentation and Closing Phase

A comprehensive documentation detailing the research and development process as well as the project outcome will be defined in the following project deliverables:

- Final Project Report
- Project Presentation

3.2.1.2 Product Deliverables

The final outcomes for this project will be as listed below:

- HTR model source code with documentation
- Fully functional AHIS with a user-friendly interface connected to a HTR
- AHIS User Manual
- Testing Plan

3.2.2 Characteristics and Requirements

The primary objective of the AHIS project is to create and introduce a comprehensive system that improves healthcare delivery by streamlining patient administration and providing better patient care using advanced data management technology. The AHIS will integrate seamlessly with currently existing healthcare technologies, guaranteeing smooth compatibility and effective data exchange.

3.2.2.1 In-Scope and Out-of-Scope Requirements

To accommodate the growing healthcare data, the system would be designed so it would be able to handle the increasing amount of patient data and healthcare information. An user-friendly user interface will make it easier for healthcare professionals to interact with the database efficiently. Other important functional requirements consist of improving the HTR model to reach at least 90% accuracy, ensuring secure management of patient data, efficient scheduling of patient appointments, and thorough medication management. Non-functional requirements center on ensuring strong data privacy and security, fast performance, and proper authentication and access controls to ensure accessibility.

The AHIS is designed with specific limitations in its scope of functionality. It will not produce or offer any medical diagnoses for patients, nor will it prescribe or manage any medical treatments for those who are hospitalized. The system's setup, including software and application configuration, will not be conducted

by our team. Additionally, the AHIS is not equipped to perform any sophisticated data analysis, with the exception of utilizing machine learning for the purpose of text recognition.

3.2.2.2 Assumptions and Constraints

The design and functionality of the AHIS are based on several key assumptions which includes the access to top-notch cameras in order to scan documents with precision and permission from patients to utilise their data as the system relies heavily on patient data to function effectively whereby without access to patient records, the team cannot create accurate health profiles, track medical histories, or provide timely interventions when needed. Another belief is that the finished project will be easily accessed on user devices, guaranteeing simple access and implementation.

Additionally, there may be several potential limitations that can affect the efficiency and implementation of the AHIS. These constraints are divided into three main categories: Resource, Technical, and Operational limitations. Resource limitations emphasize that the project's scope may be restricted by the resources availability to the team. Technical constraints suggest that the hardware that the team possess currently have restricted computing abilities which could result in inadequate hardware processing power for enhancing and advancing the HTR model. Potential obstacles to operations involve possible opposition to alterations in system processes and challenges in aligning with current technologies and protocols.

The project will work around resource, technical, and operational limitations, taking into account budget constraints, compatibility with existing systems, and complex healthcare regulations. A Requirement Traceability Matrix (see Appendix A) links each requirement to its associated deliverable, guaranteeing clarity and alignment during the project's lifespan.

3.2.3 Product User Acceptance Criteria

In order for the new health information system to succeed, it must adhere to the required standards for acceptance, as it plays a key role in directing the project and product development, guaranteeing that the end product fulfills the requirements of its users and stakeholders (Krawczyk, 2023).

The new AHIS must be significantly quicker for inputting data compared to the existing system, at least reducing the time by half. The AHIS should excel in deciphering and recognizing various healthcare professionals' handwriting, to efficiently convert hand-written notes to digital text with a minimum accuracy of 90%. The fact that the system will be accessed via a website and mobile app, it is required to have a quick loading time of no more than 5 seconds on a standard internet connection. Above all, it is essential for the system to simplify tasks for healthcare professionals.

The goal is for the system to assist them in accomplishing more tasks, specifically aiming for a 30% or greater rise in the volume of patient data they can manage per hour. Security is crucial, therefore the system must adhere to all current regulations to ensure the protection of patient data. The system must also be highly dependable with little to none downtime experience for maintenance. Healthcare professionals should just require a few hours of training to be able to use the system efficiently. The mobile app and the AHIS needs to be compatible with the most recent versions of the iPad, iPhone, and Android operating systems, and should be able to adapt to various screen sizes. Finally, a proficient customer service team must be accessible to address queries within a maximum of 4 hours during business hours (MDS2 - MINDMAP | Lucidchart, n.d.).

3.3 Schedule and Resource Management

3.3.1 Project Schedule

The schedule for the AHIS project outlines a detailed plan that includes all the functions, activities, and tasks needed to successfully finish the project. This project commenced on 12 March 2024 and is expected to conclude on 17 November 2024. The group will utilise the Agile Process model for the project, hence, a WBS is used to organize and define the full extent of work, including smaller tasks, to ensure all deliverables are covered. A Gantt chart visually presents the project schedule by showing task durations and key milestones (MDS2 - Gantt Chart.pdf, n.d.).

The project timeline includes all tasks and sets specific dates to indicate important deadlines. Some of the main tasks that meet the project's main requirements and user acceptance criteria are building and testing the HTR model, creating a scalable database, incorporating user authentication and access controls, developing patient registration and profile management systems, as well as setting up appointment scheduling features.

The report's appendix includes the WBS (see Appendix C), product backlog (see Appendix E), and Gantt chart (see Appendix B). This well-structured and comprehensive plan ensures that all elements of the project, such as user stories, user acceptance criteria, and main project requirements, align with the project requirements.

3.3.2 Resource Management

3.3.2.1 Personnel and Computer Time

This project includes the HTR model as its main component and a fully functional web application that is hosted online and can be accessed from any device or browser connected to the Internet. The team will be divided into 2 groups, with one group focusing on the HTR model and its integration with the web application, while the other group focuses on the front-end and back-end of the web application and MongoDB database.

The amount of time the HTR model is required to compute and recognise the handwriting within the images is greatly influenced by the dataset's size and the device running the model. Estimating the amount of computer time required to train the HTR models may not be feasible. However, predictive estimations can be developed based on algorithmic complexity, data attributes, and hardware processing capabilities. These approximations offer a preliminary schedule that can be altered and refined as more concrete information on the model's training time is obtained.

3.3.2.2 Hardware Specifications and Requirements

| Hardware | Processor Specification | Installed RAM |
|----------|--------------------------------------|---------------|
| Laptop A | 8th Gen Intel(R) Core(TM) i5-8265U | 8.0GB |
| Laptop B | 11th Gen Intel(R) Core(TM) i5-1135G7 | 16.0GB |
| Laptop C | 8th Gen Intel(R) Core(TM) i5-8250U | 8.0GB |
| Laptop D | 12th Gen Intel(R) Core(TM) i5-12500U | 32.0 GB |

Table 3.3.2-1 Hardware Specifications

The team will primarily be using their personal laptops to implement the HTR model and the AHIS. If the personal laptop of the team is not powerful enough to run the HTR model and/or the AHIS, the desktop computers in the Data Science Lab at Monash would be used as an alternative instead.

3.3.2.3 Software Specifications and Requirements

| Category | Components | Specifications |
|----------------------|---|----------------|
| Frontend Development | Web Development Platform | Angular |
| Backend Development | Database MongoDB | |
| | Runtime Environment Node.js | |
| | API Testing Postman | |
| Model Development | Deep Learning Framework TensorFlow, Keras, Open | |
| Code Development | Model Programming Language Python | |
| | Integrated Development Environment (IDE) Visual Studio Code (VSC) | |
| | Debugger Built-in debugger in VSC | |
| | Repository Host / Code Management Process | GitLab |

Table 3.3.2-2 Software Specifications

Table 3.3.2-2 showed the specifications of software components, category and their details. Half of the team is well-versed in the components used for both frontend and backend development, to begin with. The team has decided to utilize TensorFlow, Keras, and OpenCV, which are the most popular libraries for building HTR models, as commonly found on the Internet. TensorFlow offers a wide range of resources for creating and implementing machine learning models. Keras, which is now integrated into TensorFlow, provides a more straightforward way to build deep learning models like the HTR model in this project (Terra, 2020). OpenCV's main focus is on computer vision in real-time applications. The integration of these libraries enables strong growth of the HTR. It is noted that the team has decided to utilize Python for the model development due to its wide range of libraries and its status as the primary programming language in TensorFlow. However, JavaScript is the primary language for both frontend and backend development for the AHIS. Finally, we intend to utilize GitLab for our code version control. GitLab not just assists in monitoring modifications and working with team members but also integrates effectively with different Continuous Integration/Continuous Deployment (CI/CD) systems.

3.3.2.4 External Library Specifications and Requirements

| Software Components | Libraries |
|-------------------------|---------------------------|
| Deep Learning HTR Model | TensorFlow, Keras, OpenCV |
| Data Structure | Pandas, Zipfile, NumPy |

Table 3.3.2-3 External Software Libraries Specifications

Table 3.3.2-3 displays the third-party libraries that will be used in every section of the software. OpenCV is a software library for computer vision that helps with preparing images containing handwriting. This

process is crucial as it assists in standardizing the input data, leading to significant enhancements in the model's accuracy (Compare OpenCV vs Tensorflow | Techjockey.com, n.d.). TensorFlow makes it possible to create and train machine learning models on a massive scale, whereas Keras provides a simple interface for building NN, making the process easier. Finally, Pandas is necessary for manipulating and analyzing data, Zipfile is primarily used for extracting data from zip files, and NumPy helps with handling large arrays and matrices essential for numerical calculations.

3.3.2.5 Project Management Tools

| Category | Components Tools | |
|------------------|--|--|
| Code Development | Code Version Control GitLab | |
| Schedule | Schedule Management Gantt Chart | |
| | Task Allocation Google Sheet | |
| Communication | General Communication Whatsapp, Zoom | |
| | Communication with Supervisor Discord, Email, Zoom | |
| | File/Document Storage System Google Drive | |

Table 3.3.2-4 Project Management Tools

Table 3.3.2-4 lists the project management tools utilized by the team to guarantee effective coordination and monitoring throughout the project's lifespan. GitLab is utilized for controlling code versions which is important for handling alterations to the project's codebase, and preserving a record of code modifications. Gantt Chart is used for visualizing project timelines, monitoring progress, and organizing tasks throughout the project, while Google Sheet acts as a straightforward and efficient tool for delegating tasks, keeping track of deadlines, and supervising task completion for each member. WhatsApp has been selected for team communication on a daily basis, enabling fast messaging and virtual meetings albeit Zoom has been used for team meetings. Discord is used for more formal or targeted discussions with supervisors. However, Google Drive remains the main storage location for project files and documents, guaranteeing team members can easily reach the most up-to-date versions of all materials and documents. Together, these tools create a complete project management suite that assists with all parts of the project, such as development, scheduling, communication, and documentation. Utilizing these tools allows the team to stay organized, improve teamwork, and keep the project on target to achieve its objectives.

3.4 Project Organisation

3.4.1 Process Model

For this project, the team has chosen the Agile methodology approach in managing the project life cycle, particularly utilizing a framework called Scrum. With Agile, the project is divided into several smaller dynamic phases called sprints that allow continuous improvement in each phase to deliver an end product that meets and satisfies the stakeholder requirements. Agile is suited for our project as it offers the adaptability to meet any sudden changes or added requirements from our stakeholder during

development. This ensures that the team can flexibly and swiftly address any needed adjustment incrementally.

Moreover, the iterative nature of Agile allows the team to incorporate stakeholder feedback for continuous improvement after each sprint through sprint reviews with demo sessions. This approach is particularly significant for our project in regarding the user interface, as it helps the team to note down essential features needed to improve the health information system. Enhancing the system usability, ensuring efficient and easy navigation for healthcare professionals during usage.

Additionally, with Agile, the team is able to detect potential risks early during development, allowing the team to strategize risk response timely and address them promptly. This is advantageous for the team as early detection of risk helps the team to plan and allocate resources effectively such as time and effort in areas that are needed to mitigate the risks, ensuring the success of the project without compromising the quality of the product.

3.4.2 Project Responsibilities

A clear definition of project roles and responsibilities for each member is crucial as it helps ensure mutual understanding of each team member's work expectations. Establishing work boundaries reduces the risk of potential confusion and conflicts amongst the members and avoids accidental overlapping of work. With that, it leads to an increase in team overall productivity and efficiency, ensuring smooth progress throughout the project development with minimum miscommunication. Moreover, clearly defined roles and responsibilities improve the team's capability to track the progress of the project effectively. It simplifies the evaluation of every stage and assignment, making it easier to monitor the advancement.

The table below shows each team member's primary role and responsibilities throughout the project.

| Name | Roles | Responsibility |
|----------------------|-------------------|---|
| Foo Kai Yan | Project Manager | Develop project plan, outlining tasks, resources and timelines Monitor team and project progress Provide constant update on project progress to stakeholder Assess and manage risk management Ensure the project is delivered on time |
| Eunice Lee Wen Jing | Quality Assurance | Plan and implement testing Identify errors and potential problems within software Document test progress and results Ensure positive user experience |
| Alicia Quek Chik Wen | Technical Lead | Oversee the technical aspect of the project Determine suitable methodology and technologies to use |
| Jesse Yow San Gene | Technical Lead | Implement the software Guide members in development and design Ensure software components works |

Table 3.4.2-1 Team member's role and responsibilities

The project is supervised by Dr Muhammad Fermi Pasha, who is our supervisor that will oversee all aspects of the project. The details of each major component project function and activities with a clear distribution of responsibility amongst the team members have been outlined in the Product backlog in Appendix E.

3.5 Risk Management

Risk management is a crucial aspect of any project that involves the identification, analysis, and mitigation of potential risks that could adversely affect the project's outcomes. Effective risk management ensures that risks are systematically addressed to minimize their impact that allows the project to progress smoothly and achieve its objectives. By anticipating possible challenges and implementing proactive measures, risk management helps maintain project timelines, budgets, and quality standards.

Process for identifying, analyzing, and managing risks

Identification: Risks will be identified through brainstorming sessions, meetings with team members and discussion with supervisor to pinpoint potential risks. Team members will regularly review project milestones and deliverables to detect potential risks early. Additionally, feedback from initial testing phases and user trials will be incorporated to identify overlooked risks. and to refine the risk management strategies. This iterative process allows for continuous improvement and adaptation to new challenges as they arise.

Analysis: Identified risks will be assessed based on their potential impact and likelihood. This involves categorizing risks as high, medium, or low in terms of severity and probability. This allows the group to understand which risks take precedence over others and to allocate resources appropriately. High-impact and high-probability risks will be prioritized for immediate action, while low-impact and low-probability risks will be monitored with less urgency. This approach ensures that the most critical risks are addressed first which reduces the potential for significant project setbacks. A SWOT analysis (see Appendix I) is also used to identify the project's strengths, weaknesses, opportunities and threats.

Management: Strategies for managing risks will include mitigation, transfer, acceptance, or avoidance. Each risk will be assigned to designated group members depending on their roles that are responsible for monitoring and implementing the risk response plan. Regular risk mitigation meetings will be scheduled to ensure all team members are aware of the current risk status and the actions being taken. Developing contingency plans will be a key aspect of risk management that ensures that the team is prepared to address unforeseen events effectively. This will outline specific actions to be taken if identified risks materialize which minimize the impact on project timelines and objectives if risk cannot be avoided or mitigated.

Monitoring and Review: The risk management process will be ongoing with regular reviews and updates to the risk register. New risks will be added as they are identified and existing risks will be re-evaluated as the project progresses. Progress against risk management plans will be reported in weekly project status updates to maintain visibility and accountability. Constant monitoring and proactive risk management will be crucial throughout the project lifecycle to ensure that potential threats are identified and addressed in a timely manner. Team members will remain vigilant to actively seek out new risks and

assess their potential impact on project outcomes. Regular reviews of the risk register will allow for the identification of emerging risks and adjustments to risk management plans as needed.

A complete and detailed Risk Register can be found in Appendix H.

3.6 Stakeholder Analysis

The stakeholder analysis identifies all key stakeholders involved in the project, outlines their roles, communication methods, frequency of updates, report formats and assigns ownership for each communication task. This ensures that all parties are informed, engaged, and able to contribute effectively to the project's success. We have identified a few main key stakeholders:

Project Team: In the team of 4, specific roles are given to each member. The main goal is to finish deliverables successfully and these roles allow the team to leverage their individual strengths where all aspects of the project are ensured to be well-managed. The team has assigned specific roles to its members: Kai Yan as the project manager, Eunice as the QA specialist, and Alicia and Jesse as the technical leads (IT support team). These responsibilities enable us to use our unique skills and guarantee that every part of the project is properly handled.

Project Supervisor: Dr. Muhammad Fermi Pasha is our project supervisor. While he is not directly participating in our project, he still plays a crucial role in advising the team. He offers crucial guidance and advice that is necessary for the project team. His input and observations are essential for the project's successful outcome. Thus, his contribution is significant to the success of this project.

Teaching Team: The teaching team consists of Ms Kamala, Mr Soo Wooi King and Dr Vishnu. Even though they are not directly participating in the project, they offer critical oversight and support throughout the project. They help ensure that our project aligns with the objectives and learning outcomes of our unit by offering regular feedback, assesses our progress and evaluates our deliverables.

End User: The end users are the ultimate beneficiaries of our project. Their detailed feedback is crucial for the iterative development and refinement of our product. They provide insights into the usability and functionality of the system, helping us identify and address any issues. Regular presentations and feedback sessions with end users ensure that their needs and expectations are being met, which is vital for the project's success and relevance.

Project Sponsors: Project sponsors are responsible for providing the necessary funding and resources for our project. They are interested in the project's financial health and general advancement of the project. We regularly update them through meetings and emails to maintain transparency on the project's progress and financial expenditures. Their support is essential for maintaining the project's momentum and ensuring that all necessary resources are available.

External Consultants: External consultants bring specialized expertise and insights that are invaluable for specific aspects of the project. They provide advice on technical, operational or strategic issues that may arise during the project lifecycle. Meetings and emails are used to communicate with them as needed. Their consultancy reports help us make informed decisions and enhance the quality and effectiveness of our project.

3.7 Stakeholder Communication Plan

The stakeholder communication plan ensures that all stakeholders are kept informed and involved throughout the project. It outlines the communication techniques, update schedules, report structures, and designates responsibility for every communication task. This plan includes regular status reports, progress meetings, and feedback sessions tailored to each stakeholder's needs.

For the project team, bi-weekly meetings and status reports will keep everyone aligned and address any issues promptly. Meetings can occur in person or virtually using Zoom or Discord. A communication strategy is outlined in appendix F, which includes only the project team and supervisor. Bi-weekly updates will be provided to the project supervisor for guidance and feedback. Meetings will take place via Zoom or Discord. The teaching team will be updated monthly through presentations and feedback reports to ensure the project aligns with educational objectives and grade our assessments based on the learning outcomes. This will be evaluated through grading our assessments or our presentation. Project sponsors will receive monthly financial and progress reports to stay informed and maintain transparency for ongoing support. End users will provide feedback through monthly presentations that helps us refine the product iteratively. External consultants will be engaged as needed through meetings and emails, with consultancy reports providing valuable insights.

The comprehensive stakeholder communication plan can be found in Appendix G.

3.8 Project Monitoring and Controlling Mechanisms

3.8.1 Communication Plan and Task Allocation

Project monitoring and controlling is a significant part of the project life cycle, involving regular tracking and reviewing of the project's progress and performance (Johansson, 2024). This process is crucial in ensuring the project development is on track with respect to scope, time, and cost. It also addresses potential issues and deviations from the project plan identified during the monitoring stage by making proactive changes as needed (Johansson, 2024). Thus, the communication plan outlined in Appendix F shows the team monitoring and controlling activities implementation plan to ensure smooth progress throughout the project development in delivering the automated health information system successfully and on time. The activities include monthly sprint plannings, sprint reviews, sprint retrospectives, weekly team meetings, and biweekly meetings with the supervisor to monitor the project progress, team members' task progression reports, and many others for effective project monitoring and controlling.

Google Sheets, a straightforward and beneficial tool, will be utilized for monitoring and controlling task allocation by keeping record of the project tasks, assigned responsibilities, and scheduled deadline. For instance, the Product backlog in Appendix E demonstrates how Google Sheets is efficiently used within the team to monitor delegated tasks and supervise task completion status for each member.

3.8.2 Monitoring of project progress against planned milestones

With milestones representing key completion of specific components in our project, such as the implementation of the HTR model, help reflect crucial stages of the team project progress. The planned milestones allow effective monitoring of progress and keep the team accountable and on track. Thus, checkpoints at each milestone help team members, especially the project manager, to monitor deadlines and consequently stay on schedule, mitigating the risk of falling behind schedule.

Moreover, setting clear milestones helps detect potential bottlenecks that forecast potential delays in the project's progress when compared against actual progress (Importance of Using Milestones in Project Planning, n.d.). With that, it allows the project team to gain insights and make corrective informed decisions about possible schedule compression, such as working overtime to bring the project back on track and stay on schedule (Pink, 2024). Therefore, monitoring project progress against planned milestones is essential for the success of the project completion.

Such monitoring of project progress against planned milestones is integrated into each sprint, with each sprint outcome contributing to the overall achievement of the planned milestones. This is facilitated through monthly sprint plannings, sprint reviews, sprint retrospectives, weekly team meetings, and biweekly meetings with the supervisor, all of which track and ensure the project stays on course.

3.8.3 Review and audit mechanism

Review and audit mechanisms, including version control, quality assurance, and documentation, help ensure the delivery of our project is of high quality. GitLab will be utilized for version control to manage and track changes in our project's source code files and documentation. With each new change to the source code files from each team member, GitLab can track and maintain historical versions, enabling prompt revert to previous versions if needed through code review by the team (GitLab, 2023). This feature helps protect project progress from conflicts and incompatible changes. Therefore, we are able to work together and synchronize our tasks without hindering each other's advancements, while also facilitating the tracking of each team member's individual progress.

Various testing procedures will be performed during the project's lifecycle to guarantee that the final product meets the quality standards and specifications required. Eunice, responsible for QA, will ensure that all important aspects are considered during project development in accordance with the project requirements. Additionally, she will prepare for the testing and integration phase, through implementing test plans and test cases, conducting inspections, and performing reviews to detect and correct any potential errors, ensuring the software is error-free.

Google Drive, a cloud-based storage service, will be utilized to arrange and uphold thorough records of all written documents for the project. These documents consist of requirements, external designs, testing information, meeting minutes, risk reviews, and other materials. Proper documentation ensures that information is accurately recorded, allowing the team to easily retrieve it for future reference when necessary.

4. External Design

4.1 Overall System

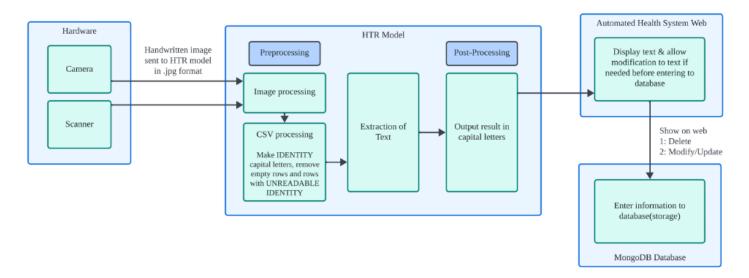


Figure 4.1-1 Overall System Relationship Diagram

Figure 4.1-1 shows the overall design of the system. The system includes the frontend interface, the HTR model, and backend storage, all connected to streamline the automated data entry process.

The front end handles the system's user interface (UI). It facilitates the capturing of handwritten notes through hardware components like cameras and scanners. These devices capture images of patient registration forms and doctor prescriptions, which are then sent to the HTR model in JPEG format for processing.

The HTR model is divided into three main stages, such as preprocessing, text extraction, and post-processing. Preprocessing of the captured handwritten text begins with image processing. This initial step enhances the quality of the image, making it suitable for subsequent text extraction. Following image processing, the system performs CSV processing to ensure data consistency. This involves converting all text to capital letters, removing any empty rows, and filtering out rows that contain unreadable identities. The core functionality of the HTR model, text extraction, then comes into play. It extracts text from the preprocessed handwritten images and converts it into a digital format. After text extraction, post-processing is conducted to further refine the text, ensuring that it is output in all capital letters, which enhances readability and consistency.

The processed text is then handled by the Automated Health Informative System Web, which provides an interface for displaying the extracted text. Users can review the text, and if necessary, modify or update it before it is saved. The web interface has the options to delete or modify the text to ensure accuracy.

Finally, the patient records, including the extracted and possibly modified text, are stored in a MongoDB database. This is to secure and organize the patient information, making it easily accessible for future use.

This comprehensive system design ensures efficient and accurate digitization of handwritten medical notes, enhancing the overall management and accessibility of patient records.

4.2 Database Schema

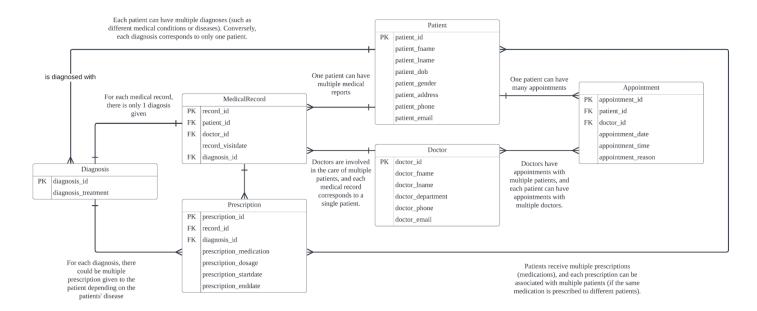


Figure 4.2-1 Database Schema

The diagram above (Figure 4.2-1) is a database schema for the healthcare system that encompasses several interconnected entities to manage patient care effectively. It includes the Patient entity, which stores patients' details and connects to multiple medical records and appointments. The MedicalRecord entity logs each patient's visit, linking to a specific patient, doctor, and diagnosis. Doctors' details are managed in the Doctor entity, which connects to multiple medical records and appointments. Diagnosis and treatment are recorded in the Diagnosis entity, associated with multiple medical records and prescriptions. The Prescription entity details medications linked to medical records and diagnoses. Finally, the Appointment entity tracks patient appointments, each linked to a patient and a doctor. This relational structure ensures comprehensive, organized, and accurate data management across the system. The database schema was designed and brainstormed based on our user stories and project requirements. It was finalized through the process of preliminary schema design, normalization, and elimination of redundancies.

4.3 User Interface

Our front end is crafted to be user-friendly and specifically tailored for healthcare professionals in clinical settings. The system focuses on efficient management of patient data and real-time access to patient histories.

At this stage, the UI design has been created using Figma. Screenshots of several important pages and key features from Figma are included to explain the design and functionality.

- the Patient Information Page (Figure 4.3-1)
- the Patient Registration Page featuring a scanning option for text recognition (Figure 4.3-2)
- the Patient Registration Page after auto-filling data (Figure 4.3-3)
- the Patient Appointment Page (Figure 4.3-4)
- the Patient Diagnosis Page which also includes a scanning feature (Figure 4.3-5)

• the Pop Up Confirmation Tab that appears in both the Patient Registration and Patient Diagnosis pages (Figure 4.3-6)

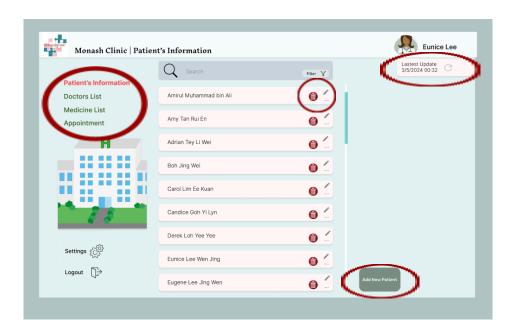


Figure 4.3-1 Screenshot of the Patient's Information Page

Patient Information Page

The Patient Information Page features a dashboard on the left side, granting access to multiple sections of the system such as Patient Information, Doctor List, Medicine List, and Appointments. For user convenience, settings and logout options are located at the bottom left. A refresh button showing the latest update time ensures users always have the most up to date data. An "Add New Patient" button enables quick entry of new patient records during registration. Additionally, action buttons for editing, deleting, or viewing more details are available for each patient record.

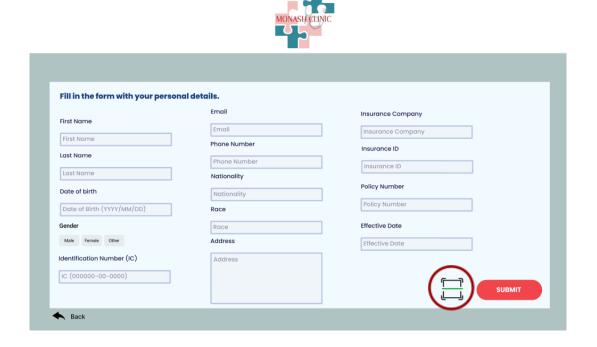


Figure 4.3-2 Screenshot of Patient's Registration Page

Patient's Registration Page

The Patient Registration Page is designed to streamline the intake of new patient information, including name, date of birth, and phone number by offering multiple input methods to increase the speed and accuracy of data entry. Users can manually input data directly into each field or use the text recognition module integrated into the system. A scanning button is located at the bottom right of the page, and plays an important role in the text recognition process. Upon clicking the scanning button, the system prompts the user to capture an image of the physical form using a phone or scanner. The interface guides the user to ensure the image is clear and properly aligned for optimal data extraction. For instance, during registration, nurses often request patients to fill out physical forms. Nurses can capture an image of the form using a phone and upload it. The system then uses the HTR model to autofill the data with high accuracy and consistency. An edit button next to each field allows users to correct or update information as needed, ensuring data accuracy.

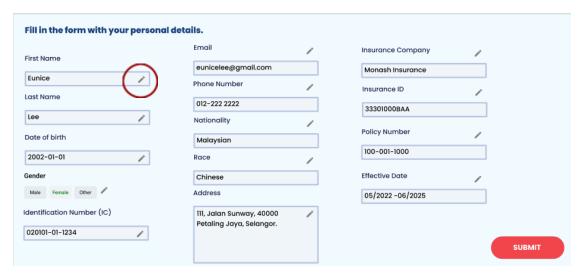


Figure 4.3-3 Screenshot of Patient's Registration Page showing patient's data is auto filled after capturing the handwritten notes or uploading image.

Once the image is uploaded, the system uses the HTR model to autofill the data with high accuracy and consistency. The page will then display the automatically populated form fields based on the scanned input. Each field has an edit button next to it, allowing users to correct or update information if needed.

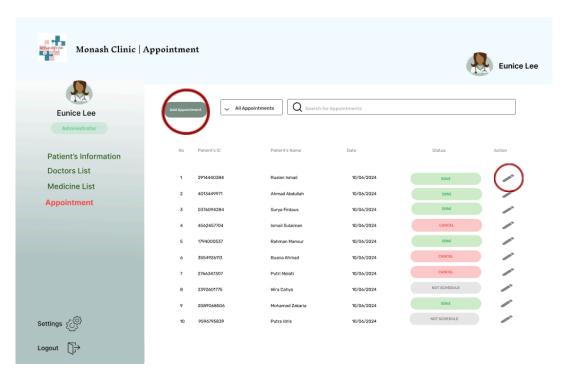


Figure 4.3-4 Screenshot of Patient's Appointment Page

Patient's Appointment Page

The Patient Appointment Page is mainly used to manage patient appointments. It displays a list of all scheduled appointments, along with an "Add Appointment" button for easily scheduling new ones. A search bar facilitates quick searching for specific appointments. The page also shows the status of each appointment, indicating whether it is done, cancelled, ongoing, or not scheduled. Additionally, an edit button is also provided beside every scheduled appointment to allow the user to make changes if needed.

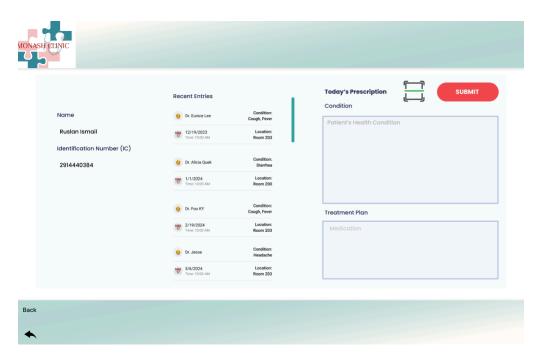


Figure 4.3-5 Screenshot of Patient Diagnosis Page

Patient Diagnosis Page

The Patient Diagnosis Page focuses on the diagnosis and prescription aspects of patient care. It displays the patient's basic information and previous diagnosis records, allowing healthcare professionals to review past interactions easily. The main section is dedicated to today's prescriptions, where current day's prescriptions can be entered and viewed. Similar to the patient registration page, the diagnosis page also incorporates the HTR model. A scanning button is also provided in the Today's Prescription Section. When the doctor clicks the scanning button, the system prompts them to capture an image of the handwritten prescriptions using a phone or scanner. The system employs the HTR model to analyze the text within the uploaded image. The recognized text is then automatically populated into the relevant fields in the Today's Prescription section. After the autofill process, the doctor can review the entered data. Each field includes an edit button, allowing for quick corrections or updates if necessary. This integration streamlines the process, making it faster and reducing manual entry errors.

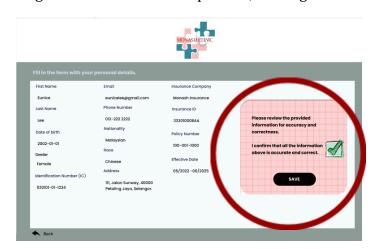




Figure 4.3-6 Screenshot of the Confirmation Tab.

Confirmation Tab

A confirmation tab appears on both the patient registration and diagnosis pages to ensure correctness of data before final submission into the system. Users are prompted to review all entered information carefully before clicking the save button to finalize and save the data to the database. This step is important for maintaining the accuracy and reliability of patient records.

By integrating these features above, the system provides a robust and user-friendly interface for healthcare professionals to manage patient information efficiently and accurately.

4.4 Data Source

The dataset obtained from Kaggle contains more than four hundred thousand handwritten names collected through charity projects and is utilized as the training dataset for the HTR model in this project. The data within the dataset consists of handwritten images in .jpg format that was broken up into test, training, and validation datasets (Handwriting Recognition, n.d.).

The dataset is all contained within a Compressed (zipped) Folder (.zip) with a size of 1.25 GB on disk. Inside the primary compressed folder, there are 3 CSV files along with 3 separate folders for testing, training, and validation purposes. The author has included the testing dataset in the testing, training, and validation folders, consisting of handwritten images in .jpg format. In contrast, the 3 csv files include the

correspondence between the handwritten image and the transcribed handwritten names. The 3 csv files consist of 2 columns each: the image filename and the transcribed handwritten names of the image (Handwriting Recognition, n.d.).

4.5 Performance

The performance of the AHIS is showcased based on 3 key factors such as the HTR model's accuracy and correctness in extracting text from images, the web-based functionalities seamlessly integrated on mobile devices and the real-time updating and management of patient records.

The ability of the HTR model to accurately extract and transcribe text from handwritten photographs is a major area of focus for our performance evaluation. Our goal is to achieve a high degree of correctness and precision, with an accuracy rate of at least 90% as our target.

The AHIS web-based features are made to be easily accessed from desktop and mobile devices. This guarantees that medical staff members can effectively retrieve and oversee patient information from any place. We stress the need of having an interface that is responsive and easy to use, minimising latency and guaranteeing fast load times on all devices. Our objective is to deliver a dependable and uniform user experience on all platforms.

Another measure of the AHIS performance is the management of data in real-time. The system is created to guarantee that patient records are promptly updated after the user makes changes, providing accurate and current information constantly. Therefore, the healthcare workers have timely access to accurate and up to date patient data that affects patient care.

To sum up, the performance of AHIS is assessed by thorough evaluations of accuracy in text extraction, accessibility on mobile devices, and management of real-time data. Our goal is to provide healthcare professionals with a high-performing, reliable, and efficient health information system.

5. Methodology

5.1 Software Tools and Algorithm

5.1.1 Programming Language

In relation to the implementation of the AHIS, Javascript and HTML will be used to develop the web-based system from the frontend to the backend development. In particular, HTML will be used to implement the web design, while Javascript will be employed to develop the functionality of the web-based application, targeting complex functions and features. Javascript is used due to the usage of the MEAN stack framework, which consists of components that support applications written in JavaScript. As for the implementation of the HTR model, Python is used to develop the model from machine learning to image processing to data processing.

5.1.2 Version Control System

For our version control system, as mentioned in chapter 3.8.2 in the review and audit mechanism section, Gitlab is used to monitor changes in our source code files and facilitate smooth collaboration amongst the team when working on their respective tasks. This is evident through working independently in each own branch where members work on different components of the project simultaneously, which is then

merged to the main branch once the component is finalized, allowing individual members' work progress to be unaffected by each other. Moreover, as GitLab maintains a detailed commit history, it allows the team to conduct thorough code reviews when needed to aid in code refinement.

5.1.3 Database System

MongoDB, a NoSQL open-source document-oriented database, will be used to collect, store, and manage patient medical-related records, including but not limited to patient medical history, diagnoses, treatments, test results, and medical appointments (Kolosky, 2024). This database system is highly suitable for our project as MongoDB efficiently handles large volumes of data and high insertion rate that meets the scalability requirement for the database of the health information system (MDS2 - Project Initial Concept and Design, Data Analysis Report.docx - Google Docs.pdf, n.d.). Moreover, given the importance of data privacy and security in healthcare, MongoDB offers many security features that can be employed to ensure compliance with the privacy and security of patient data. Such features include the implementation of user authentication in the web application and using Role-Based Access Control (RBAC) for authorization to regulate data access (MongoDB Developer Data Platform With Strong Security Capabilities, n.d.). Additionally, MongoDB has a user-friendly tool called MongoDB Compass that offers database interaction using a graphical user interface that allows the team to analyze their data in a visual environment (Adalyn, 2023).

5.1.4 Software Framework

In developing the web-based health information system, the MEAN stack framework is employed as a full-stack development framework, covering both the frontend and backend of the application system. The MEAN stack components consist of MongoDB, Express.js, Angular.js, and Node.js, all of which play a vital role in the development process as they enhance the development efficiency and cohesiveness by combining compatible tools that work well together, pre-equipped with libraries and modules that simplify common tasks (MDS2 - Project Initial Concept and Design, Data Analysis Report.docx - Google Docs.pdf, n.d.). This allows the team to concentrate more on the application's logic and function, leading to the acceleration of the development process (Stewart, 2023).

MongoDB as mentioned in chapter 5.1.3 will be the system database to store patients' health data, while Express.js, which is a backend web framework, will be used to enable interaction between the frontend and the database. Angular.js, which is a frontend framework, will be used to build the user interface of the system. Lastly, Node.js. which is a backend runtime environment, will be used to coordinate communication between the frontend and backend components.

5.1.5 Software Libraries

In building the HTR model, we will integrate several software libraries, namely Tensorflow, Keras, and OpenCV. Tensorflow and Keras are machine learning libraries that will handle the word recognition aspects of the model, covering every step of the machine learning workflow, from data processing to tuning model hyperparameters to deployment. Keras, which focuses on deep neural networks, simplifies the development and training of our deep learning model to make predictions on handwritten text. On the other hand, OpenCV is a computer vision library that contains many comprehensive sets of computer vision algorithms that will be used to handle image processing to identify handwritten text (OpenCV, 2020).

5.1.6 Model Algorithm

In building the HTR model, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Connectionist Temporal Classification (CTC) classifier algorithms are used to obtain the trained model that takes in handwritten text images for recognition that output digitized text data. CNN and RNN are deep learning algorithms suited for analyzing visual data, while CTC is a type of neural network output and associated scoring function algorithm used for training RNN (Wikipedia contributors, 2024). The diagram in Figure 5.1.6.1 shows the proposed implementation of the mode (A. Ansari, B. Kaur, M. Rakhra, A. Singh and D. Singh, 2022).

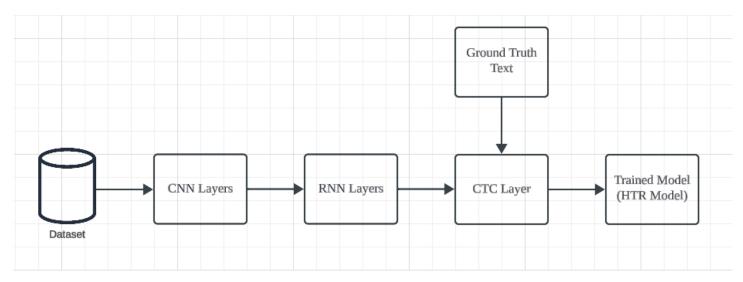


Figure 5.1.6.1 Proposed model implementation.

After the dataset has been preprocessed as detailed in chapter 5.3 and 5.4, the datasets are trained with CNN and RNN layers. The result of RNN is then passed through the CTC layer with ground truth text to get the trained model in predicting the resultant text. The CNN extracts different features from the image and identifies patterns through multiple CNN layers that output text sequences (Craig & Awati, 2024). While RNN takes in CNN output and performs text analysis where RNN takes information from prior inputs of sequential data to influence current input and output data (What Are Recurrent Neural Networks? | IBM, n.d.). The CTC layer is then used to decode the RNN output into a text and analyze the loss and backpropagate the model to update the neural network weights by calculating the loss during testing and validation with ground truth text (A. Ansari, B. Kaur, M. Rakhra, A. Singh and D. Singh, 2022).

5.2 Data Collection

As part of the research plan, the team intends to collect additional data personally in the future if required. This data will extend the existing testing dataset by including filled-in patient registration forms. The primary objective of this extra step to collect data personally is to enhance the performance of the HTR model by ensuring accurate association of data with corresponding sections and columns within the MongoDB database.

Even though these handwritten documents are important tools needed for comprehending and identifying written text, a comprehensive pre-analysis of the dataset is still required to fully grasp its dataset structure and address any potential challenges that might arise from it.

One of the main problem noted from the images is that the images containing handwritten text could have been captured in low light conditions, be blurry, or have a poor quality, which might potentially impact feature extraction accuracy and model performance (5 Common Issues Issues and Challenges in Digital Image Processing, 2019). Ensuring robustness against such variations becomes crucial for reliable text recognition hence, data analysis is done to extract vital features from the dataset that could aid in the analysis of text from images, improving data gathering techniques and the data collection process moving forward.

The pre-analysis of the data collected plays a crucial role in improving the performance of the HTR model. By thoroughly analyzing the data collected within the dataset, the team can gain insights into handwriting variations, patterns, and its potential challenges. The insights obtained could guide the team on pre-processing strategies which ensures accurate data association, and in turn, aids in creating a strong HTR model.

In the end, the training dataset is utilized for the purpose of training the HTR model, allowing the model to adapt its weights in order to make correct text predictions based on the target variable. The purpose of the validation dataset will be utilized to assess the model's efficacy. It serves as a safeguard against overfitting, where the model is excessively customized to the training data and struggles to apply to unfamiliar data. The validation dataset aids in creating a model that can effectively be applied to unseen data. After training and validating the HTR model, the testing dataset is utilized to give an impartial, conclusive assessment of its performance. It is utilized only after the model has been tuned successfully.

5.3 Data Pre-processing and Preparation

The data is in a zip file on the disk, but since the zip file is too big, code will be used to extract the data for processing and analysis. The two primary pre-processing techniques that will be utilized include CSV pre-processing and Image pre-processing, which will be detailed as follows.

5.3.1 CSV files Pre-processing

All three CSV files have a consistent structure with a total of 2 columns each, containing the image file path and the transcribed handwritten strings from the images. CSV file pre-processing includes basic data cleaning methods like removing duplicates and missing or unreadable values. In order to pre-process the 3 CSV files, if any missing values, special characters, punctuation marks, or unwanted symbols are found in the second column of the CSV files, the entire row will be deleted. However, prior to removal, the image pathway of the row will be recorded to prevent the image from being included in the sets for testing, training, and validation that are meant to refine the HTR model. The transcribed text will then be checked and converted to uppercase before being added to the database, ensuring all information is in capital block letters.

5.3.2 Image Pre-processing

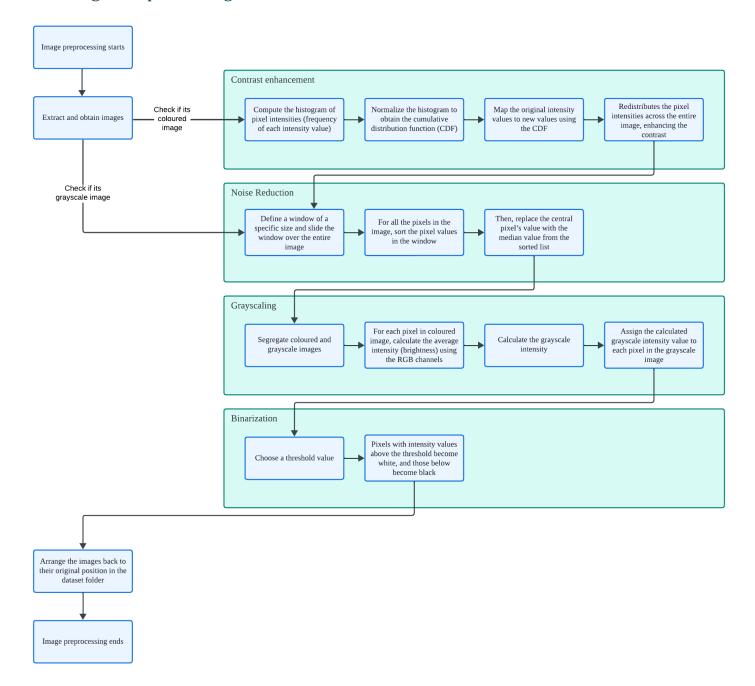


Figure 5.3.2-1 Image Pre-processing Process

The method shown in Figure 5.3.2-1 aims to enhance the image quality and streamline the computational process for better outcomes from the HTR model (KUMAR, 2021). Contrast enhancement techniques improve image quality and highlight specific features, such as handwritten text, to enable more effective analysis (Mescioglu, 2022). Noise reduction allows the removal of unwanted noise from images (Patel, 2023). Grayscaling and binarization convert colored images to grayscale and then further grayscale images to black and white. Grayscale simplifies algorithms and reduces computational requirements while binarization creates a clear contrast between text and background which helps the HTR model to identify regions of interest (Why We Should Use Gray Scale for Image Processing, n.d.).

Contrast enhancement methods modify the pixel intensity distribution in an image. Increasing the contrast will make the distinctions between dark and light areas more noticeable (Image Super Resolution Using ESRGAN | TensorFlow Hub, n.d.). Therefore, enhancing the clarity of handwritten text areas in the images would aid the HTR model in distinguishing individual characters and words for feature extraction in later analysis.

Noise reduction methods eliminate undesired elements or disruptions from an image. Clear images with less noise make it easier for the HTR model to identify handwritten text.

Converting an image to grayscale through grayscaling method involves eliminating color data, leading to a simplified image representation for processing by the HTR model. By using grayscaling, the HTR model can concentrate only on the text in the image without being influenced by different colors which in turn decrease the computational complexity of the HTR model for further processing.

Transformation of grayscale images to black and white through binarization involves setting a threshold for pixel intensities to enhance the contrast between text and background. The HTR model can effectively differentiate between text and non-text areas in the image, helping to improve character recognition accuracy.

These 4 crucial image pre-processing steps ensure consistency, reduce computational complexity, and improve the efficiency of image processing (Python | Grayscaling of Images Using OpenCV, 2019).

5.3.3 Data Preparation

Once the CSV files and the images have been processed, the relevant information from the CSV files would be compared and linked to the corresponding images to ensure that the image data is consistent and free from any inconsistencies or missing values. Furthermore, any issues with the quality of the data, such as duplicates, outliers, or incorrect entries, will be resolved through data cleaning to guarantee the accuracy and reliability of the results obtained from the HTR model.

5.4 Data Post-processing

After the images are processed by the HTR model, the text will be converted to uppercase before inputting patient information data into the database, to guarantee uniformity and ease of searching. MongoDB queries used for patient names or other relevant information can be treated in a way that is case-insensitive, allowing the database to uphold uniformity in the stored data within the database.

6. Test Planning

6.1 Test Objectives

The main objective of testing the AHIS is to thoroughly confirm the HTR model's performance and reliability (Sharma, 2019). The main goal is to guarantee that the HTR model reaches at least 90% accuracy and precision. This requires running a thorough set of tests that mimic real-life situations to ensure the model's results are consistently accurate and dependable. The primary responsibility for conducting testing activities rests with the QA. QA will ensure that the testing conducted will verify that the finalised AHIS will meet all predetermined user acceptance criteria and project requirements in addition to ensuring the accuracy of the HTR model.

6.2 Test Coverage

Examining and validating all aspects of the AHIS is crucial to assessing test coverage (Medewar, 2023). The evaluation of data input speed and accuracy will measure the efficiency of data entry testing. Accuracy in recognizing handwritten notes will assess how precisely the system interprets and converts handwritten notes to digital format.

User Experience evaluation will assess the system's general ease of use and satisfaction from the user's point of view. Additional evaluations will be done to measure the system's effect on improving the productivity of the healthcare clinic or hospital. Ensuring patient data security is extremely important, and trails will be done to confirm that all patient information is safeguarded from unauthorized access.

System uptime tests will assess the AHIS's reliability and availability to guarantee minimal downtime. Evaluating the responsiveness of the mobile app will guarantee its effectiveness and functionality on different mobile devices. Together, these coverage areas offer a thorough assessment framework to guarantee the AHIS upholds top-notch standards of quality and efficiency.

6.3 Test Methods and Cases

The team will utilize different testing methods to confirm that the AHIS is functioning correctly. Manual testing is a vital technique for evaluating the user interface and user experience. It is a method that offers valuable information on the practical usability of the system. Performance testing is an additional test technique carried out to ensure that the system fulfills efficiency and speed criteria, which are essential for ensuring a seamless workflow in the healthcare industry. Another crucial form of testing is security testing, ensuring that the system complies with strict data protection regulations to protect sensitive patient data. Usability testing assesses how easy it is to use the system and making sure healthcare professionals can easily learn and effectively utilize the system. Finally, compatibility testing guarantees that the AHIS provides a uniform experience on different devices and operating systems.

In addition to that, the team has decided to employ two different testing approaches for the HTR model: manual testing and the Model.evaluate method from Keras (Team, n.d.). This approach offers an unbiased evaluation of the model's performance by giving measurable metrics like loss and accuracy, which are essential for assessing the efficiency of the HTR model. Furthermore, this technique guarantees uniform evaluation conditions for the model by utilizing the same computation and processing methods used in training. This is essential for comparing performance across various iterations of the model. Finally, this approach is easy to put into practice and needs only a small amount of code, allowing the team to easily test and improve the HTR models. Additionally, it is important to mention that this technique has the capability to handle substantial amounts of test data in groups, providing a time-saving approach to evaluating model effectiveness that greatly benefits the team (Wikipedia Contributors, 2019). Specific testing methods for each feature designed to fulfil the project requirements can be found in Appendix A.

7. Conclusion

The report provides an in-depth explanation of the AHIS aimed at enhancing healthcare data management and accessibility. The goal of the project is to develop a web-based system that is closely linked with a mobile app, incorporating a HTR model to simplify data entry procedures, improve the user experience for healthcare professionals, and enhance efficiency in managing healthcare data.

The HTR model plays an important role in the project by converting handwritten medical notes and prescriptions into digital records stored in the database. The model aims to reach a minimum of 90% accuracy and precision, guaranteeing reliable performance in real-world scenarios. The QA team will oversee the testing phase to ensure that the AHIS meets the predetermined user acceptance criteria and project requirements, including validating the precision of the HTR model.

The project's progress and outcomes are overseen using a comprehensive WBS (see Appendix C) and a Gantt Chart (see Appendix B) to categorize and clarify the entire scope of work, including minor tasks, to make sure all deliverables are accounted for. Google Sheet is also utilized for monitoring the task allocations in report writing for each team member. The project's schedule contains milestones and precise dates to show important deadlines. The team will carefully track project progress towards planned milestones in order to remain on schedule and promptly deal with any possible delays.

The project aims to improve healthcare data management, enhance patient care, and boost efficiency in the healthcare industry. With the project supervisor's guidance and support, the team aims to effectively develop the project in the upcoming semester, guaranteeing that the AHIS fulfills stakeholders' needs and expectations.

8. Appendix

Appendix A. Requirement Traceability Matrix

| Req. ID | Requirement Description | Categories | Requirement Type | Test Category |
|---------|---|------------------------|------------------|---|
| 1 | Update existing HTR model that can use devices or scanner to scan digital or physical handwritten text of any format (print handwriting, cursive and pre-cursive handwriting) | Data, Visualisation | Functional | HTR Model Testing, Compatibility Testing, Manual Testing, Performance Testing |
| 2 | Scalable database design implemented to handle growing data | Data | Non-Functional | Performance Testing, Manual Testing |
| 3 | Patient data privacy and confidentiality are kept intact to prevent misuse of information | Security | Non-Functional | Security Testing |
| 4 | Basic health information system where the handwriting recognition system is implemented/integrated | Data | Functional | HTR Model Testing, Performance Testing, Manual Testing |
| 5 | User authentication and access control | UI, Security | Functional | Security Testing, Usability Testing |
| 6 | Patient registration and profile management | Data, UI | Functional | Performance Testing, Manual Testing, Usability Testing |
| 7 | Medication prescription management and history | Data, UI | Functional | Performance Testing, Manual Testing, Usability Testing |
| 8 | Appointment scheduling between patients and healthcare doctors | Data, UI | Functional | Performance Testing, Manual Testing |

| 9 | User-friendly interface for healthcare professionals/workers | UI | Non-Functional | Manual Testing, Usability Testing |
|------|--|-------------|----------------|--|
| 1 10 | HTR have a accuracy of 90% in recognising the handwritten text from the images | Performance | Non-Functional | HTR Model Testing |
| 11 | Healthcare workers should be able to schedule appointments for registered patients | Data, UI | Functional | Performance Testing, Manual Testing, Usability Testing |
| 12 | The system should allow doctors to initiate patient encounters based on the appointments scheduled for the day | Data, UI | Functional | Performance Testing, Manual Testing, Usability Testing |
| 13 | The system must provide a feature that enables doctors to access and review patients' medical records from previous encounters | Data, UI | Functional | Performance Testing, Manual Testing, Usability Testing |
| 14 | The system should be able to be used on different devices and operating systems | Data, UI | Non-Functional | Performance Testing, Compatibility Testing |

Table 8-1. Requirement Traceability Matrix (MDS2 - Requirement Traceability Matrix, n.d.)

Appendix B. Gantt Chart

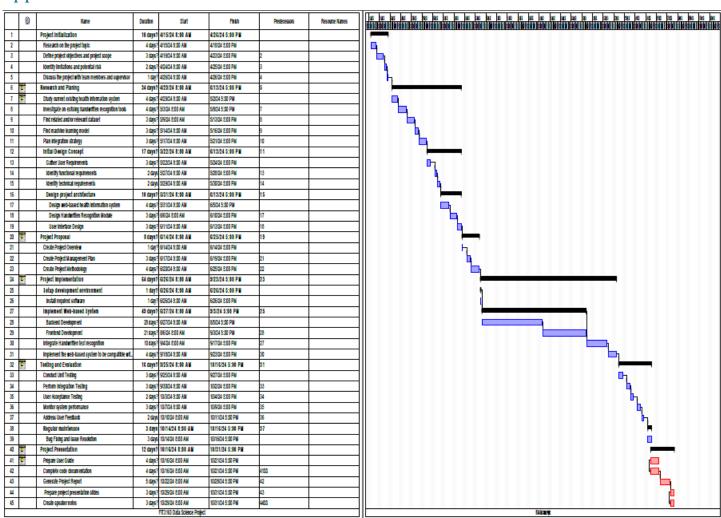


Figure 8-2. Gantt Chart (MDS2 - Gantt Chart.pdf, n.d.)

Appendix C. Work Breakdown Structure

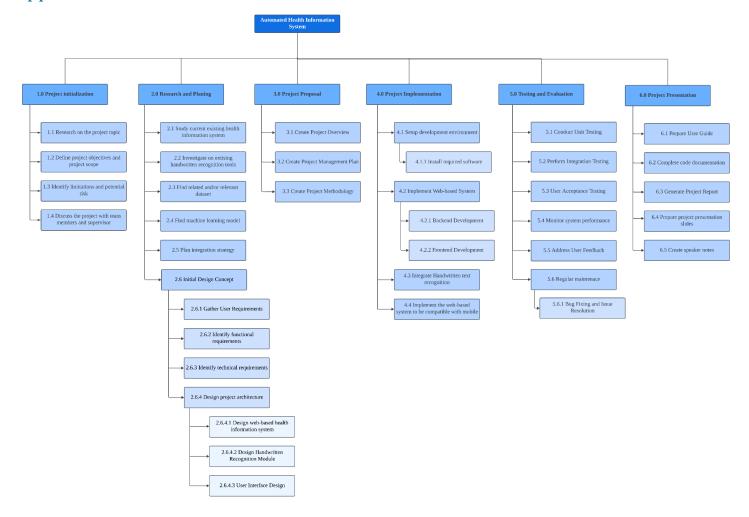


Figure 8-3. Work Breakdown Structure (MDS2 - MINDMAP - ACTUAL WBS.png, n.d.)

Appendix D. User Acceptance Criteria

| ID | User Stories | User Acceptance |
|-----|--|---|
| UA1 | As a director of a healthcare institute, I need a system with user authentication and access control, so that sensitive patient information is accessible only to authorized personnel. | All necessary healthcare workers will be given login credentials and their roles determine the restrictions on access to patient information. Unauthorized access attempts are recorded and reported to the security department. |
| UA2 | As a doctor, I want to be able to enter my patient's diagnosis more efficiently into the system whereby I can scan my written diagnosis into the database, so that I don't have to spend extra time manually re-entering it into the system. | The AHIS has a HTR model integrated to it to scan and upload doctor's handwritten diagnoses. Uploaded diagnoses are accurately converted into digital format by the HTR model which is a faster process compared to manual entry. |
| UA3 | As a nurse, I want to be able to enter my patient's information during registration whereby I can scan the patients' written name and id into the database, so that I do not need | The AHIS has a HTR model integrated to it to streamline the registration process by allowing scanning of handwritten patient information during registration, reducing patient wait |

| to let the patient wait for their turn just for their information to be added to the clinic's accurately filled with the scanned info database. UA4 As a patient, I need assurance that my personal health data and diagnosis remain times. The clinic's patient database is accurately filled with the scanned info accurately fille | ormation. and |
|--|------------------|
| personal health data and diagnosis remain security measures in place to protect | |
| confidential in order to safeguard my privacy and prevent any potential misuse of my information. | |
| UA5 As a system administrator of a healthcare clinic, I need a scalable database design that can handle increasing amounts of data without any performance degradation, ensuring that we can continue to provide timely care as our patient base grows. The database can scale horizontally we significant performance loss. | rithout |
| UA6 As a healthcare clinic pharmacist, I need a system that helps me manage medication prescriptions and history, so that I can track and verify patient medications efficiently. Authorized personnel can retrieve an prescriptions or medication informat prescribed to patients quickly and account of the prescription of the pre | ion that is |
| UA7 As a nurse, I need a user-friendly interface for our health information system, so that I can navigate and use the system easily. The AHIS will be designed so that it can easily used with minimal staff training required. | |
| UA8 As a doctor's assistant, I need to be able to help doctors to schedule appointments for registered patients, ensuring that their care is organized and timely. Appointments between patient and d be scheduled without errors. AHIS with callendars in real-time. | ll update |
| UA9 As a doctor, I want the system to allow me to initiate patient encounters based on the day's scheduled appointments, so that I can manage my time and patient flow effectively. Doctors can initiate patient encounter from the appointment schedule displayed the AHIS. | |
| UA10 As a healthcare worker, I want a system that is compatible with various devices, so that I can access patient information regardless of the technology I'm using. AHIS can meet all required performant standards across all platforms on any with any operating system. | |
| Table 8-4. User Acceptance Criteria | |

Appendix E. Product Backlog

| - | | | D | | - ' | | | · · |
|-----|--|---|---|-----------------|---------------|-----------------|------------------|--------------|
| ID | User Stories | User Acceptance | Major Activities | Time Estimation | Sprint | Progress Status | Person In Charge | Cooperated I |
| | | Investigate how login credentials function | 1 Week | 1 | In-Progress ▼ | Kai Yan 🔻 | Alicia | |
| | As a director of a healthcare institute, i | All necessary healthcare workers will be | Investigate encryption technique | 1 Week | 1 | In-Progress ▼ | Kai Yan ▼ | Alicia |
| | | given login credentials and their roles determine the restrictions on access to | Select appropriate encryption technique | 1 Week | 2 | Not Started ▼ | Kai Yan ▼ | Alicia |
| PB1 | access control, so that sensitive patient | nations information. In outhonized a sees | Develop role-based access control (RBAC) system | 2 Weeks | 2 | Not Started ▼ | Kai Yan ▼ | Alicia |
| | information is accessible only to authorized | attempts are recorded and reported to the | Implement user authentication system | 2 Weeks | 3 | Not Started ▼ | Kai Yan ▼ | Alicia |
| | personnel. | security department. | Set up security logging and alerting | 2 Weeks | 4 | Not Started ▼ | Kai Yan | Alicia |
| | | | Perform system security testing and finetune it if needed | 3 Weeks | 4 | Not Started ▼ | Kai Yan | Alicia |
| | | | Research on Handwritten Text Recognition (HTR) Model | 1 Week | 1 | In-Progress ▼ | Jesse ▼ | Eunice |
| | | | Collect dataset to train, test and validate the HTR model | 1 Week | 1 | In-Progress ▼ | Jesse ▼ | Eunice |
| | As a doctor, I want to be able to enter my | The AHIS has a HTR model integrated to it | Train the HTR model with training dataset | 4 Weeks | 2 | Not Started ▼ | Jesse ▼ | Eunice |
| | patient's diagnosis more efficiently into the | | Evaluation HTR model with validation dataset | 2 Weeks | 2 | Not Started ▼ | Jesse ▼ | Eunice |
| PB2 | system whereby I can scan my written diagnosis into the database, so that I don't | diagnoses. Uploaded diagnoses are accurately converted into digital format | Test and retrain HTR model to optimize model accuracy | 2 Weeks | 3 | Not Started 🔻 | Jesse ▼ | Eunice |
| | have to spend extra time manually | by the HTR model which is a faster process compared to manual entry. | Develop scanning and upload feature | 4 Weeks | 3 | Not Started ▼ | Jesse 🔻 | Eunice |
| | re-entering it into the system. | | Integrate scanning and upload feature to AHIS | 2 Weeks | 4 | Not Started ▼ | Jesse ▼ | Eunice |
| | | r | Integrate HTR model to AHIS | 2 Weeks | 4 | Not Started ▼ | Jesse 🔻 | Eunice |
| | | | Monitor performance of HTR model in AHIS | 3 Weeks | 4 | Not Started ▼ | Jesse 🔻 | Eunice |
| | | | Research on Handwritten Text Recognition (HTR) Model | 1 Week | 1 | In-Progress ▼ | Eunice 🔻 | Jesse |
| | A | | Collect dataset to train, test and validate the HTR model | 1 Week | 1 | In-Progress ▼ | Eunice 🔻 | Jesse |
| | as a nurse, I want to be able to enter my patient's information during registration | | Train the HTR model with training dataset | 4 Weeks | 2 | Not Started ▼ | Eunice 🔻 | Jesse |
| | whereby I can scan the patients' written | | Evaluation HTR model with validation dataset | 2 Weeks | 2 | Not Started ▼ | Eunice • | Jesse |
| PB3 | name and id into the database, so that I do | | Test and retrain HTR model to optimize model accuracy | 2 Weeks | 3 | Not Started ▼ | Eunice • | Jesse |
| | not need to let the patient wait for their | patient wait times. The clinic's patient | Develop scanning and upload feature | 4 Weeks | 3 | Not Started ▼ | Eunice 🔻 | Jesse |
| | turn just for their information to be added | database is accurately filled with the | Integrate scanning and upload feature to AHIS | 2 Weeks | 4 | Not Started 🔻 | Eunice 🔻 | Jesse |
| | to the clinic's database. | scanned information. | Integrate HTR model to AHIS | 2 Weeks | 4 | Not Started 💌 | Eunice 🔻 | Iesse |
| | | | Monitor performance of HTR model in AHIS | 3 Weeks | 4 | Not Started 🔻 | Eunice 🔻 | Tesse |
| | | | Investigate how login credentials function | 1 Week | 1 | In-Progress ▼ | Kai Yan ▼ | Alicia |
| | As a patient, I need assurance that my | | Investigate encryption technique | 1 Week | 1 | In-Progress ▼ | Kai Yan ▼ | Alicia |
| | | aelth data and diagnosis remain al in order to safeguard my The AHIS have adequate encryption and security measures in place to protect Develop role-based access control (RBAC) system | | 1 Week | 2 | Not Started ▼ | Kai Yan ▼ | Alicia |
| PB4 | confidential in order to safeguard my | | | 2 Weeks | 2 | Not Started ▼ | Kai Yan ▼ | Alicia |
| | | | Implement user authentication system | 2 Weeks | 3 | Not Started ▼ | Kai Yan | Alicia |
| | my information. | Ī | Set up security logging and alerting | 2 Weeks | 4 | Not Started ▼ | Kai Yan | Alicia |
| | | | Perform system security testing and finetune it if needed | 3 Weeks | 4 | Not Started ▼ | Kai Yan | Alicia |
| | | | Investigate different database structures | 1 Week | 1 | In-Progress ▼ | Alicia 🔻 | Kai Yan |
| | As a system administrator of a healthcare | | Select appropriate database structure | 1 Week | 2 | Not Started ▼ | Alicia 🔻 | Kai Yan |
| | clinic, I need a scalable database design that | | ociect appropriate database su deture | 1 WCCK | - | Not Stalled + | Tillela | Itai Idli |

Figure 8-5. Product Backlog (MDS2 - Product Backlog, n.d.)

Appendix F. Communication Table

| Meetings | Description/Objective | Individuals Involve | Communication Channels |
|---|--|--|--|
| with Supervisor seek feedback for enhancement and acquire guidance when needed. | | Dr Muhammad Fermi Pasha, Project Team Members | Online via Zoom or physically on campus |
| Weekly Team Meeting | Conduct discussions on individual members' progress reports, status reports, forecast reports, and risk reviews to ensure the team is on the same page and on track with the project schedule. | Project Team Members | Online via Zoom |
| Monthly Sprint Planning | Plan and estimate the work to be done and time needed for the upcoming sprint, and delegate tasks among the team members. | Project Team Members | Online via Zoom |
| Monthly Sprint Review | Demo work outcome to stakeholder and evaluate the completion and/or incompletion of user stories if any to determine any future adaptations needed. | Dr Muhammad Fermi Pasha, Project Team Members | Online via Zoom |

Table 8-6. Communication Plan (What Is Scrum? - Scrum Methodology Explained - AWS, n.d.)

Appendix G. Stakeholder Communication Table

| Stakeholders | Description | Medium | Frequency | Report Format | Owner |
|---|---|---|----------------------------------|---|----------------------|
| Project Team Members | Report project updates for each team member, check understanding of certain topics and addressing any issue encountered | Meetings, email, messages (Discord) | ail, Bi-weekly Status Reports | | Kai Yan |
| Project Supervisor (Dr Fermi) | Progress reports including issues encountered and upcoming tasks | Meetings, emails, messages (Discord) | Bi-weekly | Status Reports | Kai Yan |
| Teaching Team | Illustrate plans for project and later on demonstrate finished product | Presentation | Monthly | Teaching Team Feedback Reports | Project Team |
| Project Sponsors | Provide funding and resources, and update on the project's progress and financial status | Presentation /email | Monthly | Financial and Progress Reports | Kai Yan |
| IT Support Team | Deal with technical issues, software installations and system integrations | Meetings, messages (Discord, Whatsapp) | As needed | Technical Support Logs | Alicia & Jesse |
| Quality Assurance Specialist | Conduct testing and validation of the project to ensure it meets quality standard | Meetings, messages (Discord, Whatsapp) | Bi-weekly | Test Reports | Eunice |
| End Users | User giving detailed feedback on our project and end product | Presentation | Monthly | User Feedback Reports | Project Team |
| External Consultants Provide expert advice and insights on specific aspects of the project | | Meetings, emails | As needed | Consultanc y Reports | Project Team |

Table 8-7. Stakeholder Communication Plan

Appendix H. Risk Register

| ID | Risk Description | Risk Category | Root Cause | Trigger | Probability | Impact | Owner | Mitigation |
|-----|--|-----------------------|---|--|-------------|--------|------------|--|
| 1. | Project Delays | Project Management | Poor Time Management | Unexpected technical and non technical issues, starting project late | Medium | High | Kai Yan | Ensure group members prioritize high priority tasks and ensure all tasks is completed on time |
| 2. | Hardware Issues | Technical | Faulty or Old Hardware | Hardware malfunctions or failure | Low | Medium | Jesse | Regular hardware maintenance or repair malfunctioned hardware |
| 3. | Software Compatibility | Technical | Differences in Software Versions or Dependencies | Incompatibility error when integrating software components or updates | High | High | Alicia | Conduct compatibility testing and ensure chosen software is compatible when integrating with hardware |
| 4. | Data Privacy Breach | Ethical/ Technical | Poor Security Measures | Unauthorized access or data breach incident | Medium | High | Eunice | Implement strong encryption method and conduct regular security audits |
| 5. | Inaccurate Model | Technical | Poor Model Training | Low accuracy during testing | Medium | High | Jesse | Use cross-validation and continuously improve the model with more data and better algorithms. |
| 6. | Insufficient Data Collection | Data Quality | Incomplete or Missing Data | Incomplete data found in dataset during preprocessing | Medium | High | Kai Yan | Conduct thorough data cleaning (remove rows with incomplete data etc) |
| 7. | Team Member Availability | Project Management | Scheduling Conflicts | Delays in task completion | Medium | Medium | Kai Yan | Develop a flexible project schedule |
| 8. | Miscommunic ation | Project Management | Misunderstan ding Between Team Members | Misunderstanding s, missed deadlines | Low | Medium | Eunice | Ensure that all teammates understand and are on the same wavelength |
| 9. | Insufficient Training Data Quality | Data Quality | Low Quality Data | Low model performance | Medium | High | Kai Yan | Ensure data quality through validation |
| 10. | Supervisor Unavailability | Project Management | Scheduling Conflicts or Personal Issues | Delayed feedback or approvals | Low | High | Eunice | Schedule regular check-ins in advance and request for supervisor's advice/approvals earlier |
| 11. | Difficulty in model integration into system | Technical | Compatibility Issues | Errors during system integration testing | Medium | High | Alicia | Ensure model is of compatible version with system or else request advice from supervisor |
| 12. | Unexpected | Technical | Loss during | Corrupted data or | Low | High | Jesse | Ensure that all work |

| Data Loss testing o saving w | 1 | | and project versions are backup in Google Drive |
|------------------------------|---|--|---|
|------------------------------|---|--|---|

Table 8-8. Risk Register

Appendix I. SWOT Analysis

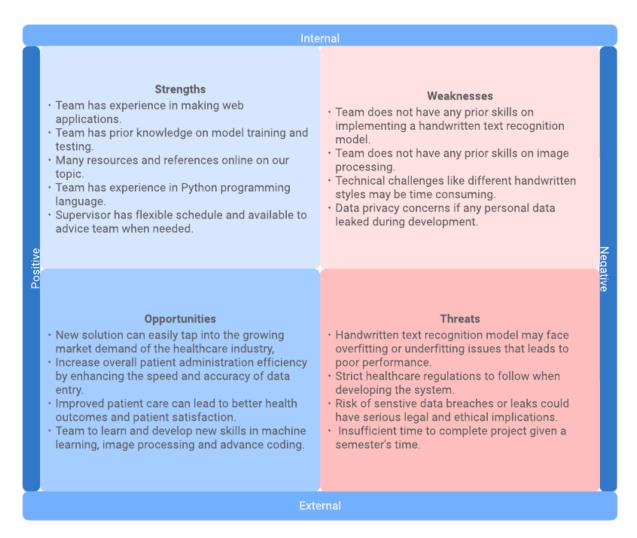


Table 8-9. SWOT Analysis

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10. Acknowledgement

I acknowledge the use of Microsoft Copilot (https://copilot.microsoft.com/) to generate materials for background research and self-study in the process of completion of this assessment. I entered the following prompts on 25 May 2024:

- > Provide the common pre-processing steps for images with explanation on why it is done as so
- > Explain Product User Acceptance Criteria
- ➤ What is a Product Backlog and its usage
- > Explain Test Objectives, Test Coverage, Test Methods and Test Cases

The generated output from the artificial intelligence was adapted, modified and used for some of the final response.