	SWOT Analysis				
No.	**Research Title**	**Strengths**	**Weaknesses**	**Opportunity**	**Threats**
1	AI-backed OCR in Healthcare	- 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. - This research article talks abit on CNN and RNN architecture that we have used in our project for further reference.	- 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. - We faced this challenges in our project where we believe that a bigger dataset will help improve the overall accuracy of recognition of text	- 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.	- Specific linguistic nuances of Romanian handwriting may present additional challenges that need to be addressed to ensure comprehensive recognition capabilities.
2	Increasing The Accuracy Of Handwriting Text Recognition in Medical Prescriptions With Generative Artificial Intelligence	- 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. - This research article leverages the combine usage of CNN and CTC architecture for processing and recognizing images of text. This again is used for further reference in our project.	- 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.	- Further research in generative artificial intelligence for personalized information selection in medical prescriptions. - 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.	- The effectiveness of generative AI depends on the availability 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.
3	An Online Cursive Handwritten Medical Words Recognition System for Busy Doctors In Developing Countries For Ensuring Efficient Healthcare Service Delivery	- 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. - This study uses LTSM that gives a better understanding of its theory and implication although not exactly the same. We are able to understand its usage further in our pre built HTR model.	- Further improvement to ensure reliable and consistent performance. - Relies on a relatively small dataset. - Smartpen application is still in the concept stage.	- Technique can be applied to other industries such as education, where tools like smartpens can be used to digitize handwritten notes, providing similar benefits.	- 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.
4	Optical Character Recognition System in Healthcare and Hospital Management	- 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. - Our HTR model is able to handle the various handwriting styles. We used this case study's simple techniques to test its boundaries.	- 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.	- 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.	- 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. - We also found the same results that poor handwriting styles lead to more inaccurate recognition.
5	MediCrypt: Survey on Automated Recognition of Handwritten Medical Prescriptions for Enhanced Healthcare Efficiency	- High accuracy rates ranging from 89.5% to 95-98%. - Enhances patient understanding and overcome language barriers.	- 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. - We also found that bad image quality also influences our model's performance hence we ensured good image quality is used in our project.	- 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.	- High-resolution capture techniques and the use of better cameras with proper lighting conditions are needed as poor images can reduce text extraction accuracy. - Our HTR model also depends on proper lighting conditions. Increasing lighting conditions to remove background shadows has showed great effect on our HTR model's accuracy.
6	Interpreting Doctor Notes using Handwriting Recognition	- Improved accuracy of prescription identification using CNN and RNN. - Recognition and translation of handwritten medicine names accurately. - Implementation of CNN and RNN has greatly increased our understanding of the combination of these deep architectures that shows that this combination can obtained great results.	- 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	- Collaboration with pharmaceutical companies could provide access to real-time updates on medication databases.	- 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.

7	Towards an On-line Handwriting Recognition Interface for Health Service Providers using Electronic Medical Records	- Improved handwriting recognition interface for physician workflow and patient care. - Low cost deployment of the handwriting recognition interface due to open-source technologies.	- 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. - We also have faced challenges in recognzing certain symbols in our forms example @, ! ?.	- Exploring advanced machine learning and AI algorithms that can adapt to different handwriting styles, resulting in better recognition results.	- 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.
8	Development of an optical character recognition pipeline for handwritten form fields from an electronic health record	- 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.	- 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.	- 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.	- 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.
9	Optimization of a Handwriting Recognition Algorithm for a Mobile Enterprise Health Information System on the Basis of Real-Life Usability Research	- 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.	- 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.	- 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.	- 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.
10	Recognition of Handwritten Medical Prescription Using Signature Verification Techniques	- 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	- 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.	- 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.	- 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.
11	Building Structured Personal Health Records from Photographs of Printed Medical Records	- 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.	- 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. - We found that image quality has a great impact in our HTR's accuracy during the testing phase.	- 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. - We learned from this research paper that building a good structure patient form helps with the preprocessing process as it minimizes the usage of complex algorithms.	- 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. - Similar defects with our HTR model where if handwriting is unclear or image quality is extremely low then our HTR recognition accuracy will be low.

12	A Machine Learning-based Approach to Vietnamese Handwritten Medical Record Recognition	- Ability to effectively recognize words with a massive number of labels. - Not requiring segmentation at the character level. Not requiring segmentation at the character level. - Ability to process long strings.	- 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. - We also faced this challenge where writing outside the given space will affect the other sections accuracy of recognizing those texts. We solved this by writing a clear instructions on our forms to ensure any patient filling up will only write in the given space.	- 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.	- 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.
13	Handwritten Text Recognition using Deep Learning	- Achieves over 90.3% accuracy in text recognition, especially for less noisy inputs. - CNN layers effectively extract 2D features essential for recognizing handwritten text. - RNN layers, particularly LSTM enhances the model's ability to remember relevant information, improving recognition of complex handwriting.	- Accuracy is highly reliant on training dataset quality, poor data can hinder results. - The system struggles with cursive handwriting leading to misclassification. - The multi-layer architecture complicates training and requires significant computational resources.	- Training on more diverse datasets could enhance generalization capabilities. - Exploring embedding models and advanced data augmentation may improve recognition accuracy. -The technology can be adapted for digital note-taking and automated transcription services.	- Evolving handwriting recognition techniques may outpace the current model. - Reliance on large datasets raises privacy and security concerns that limits adoption. - A competitive landscape of existing handwriting recognition solutions could threaten adoption if the model does not continuously improve.
14	A Machine Learning-based Approach to Vietnamese Handwritten Medical Record Recognition	- Employs architectures like CNNs and LSTMs which are effective for image classification and sequence prediction. - Demonstrates superior performance over word-level classification by reducing complexity and improving accuracy with a smaller vocabulary size. - Utilizes the diverse IAM Handwriting Dataset enhancing the model's ability to generalize across various handwriting styles.	- Limited vocabulary size (50 words) may hinder generalization to a broader range of handwritten text. - The model struggles with cursive handwriting, leading to errors in character extraction and reduced recognition accuracy. - Training deep learning models like VGG and RESNET requires substantial computational resources posing barriers for rapid prototyping.	- Incorporating language models could enhance accuracy in character sequence predictions, addressing reliance on visual classification. - Increasing dataset size and diversity may improve model performance and feature representation across handwriting styles. - The technology has potential applications in education, archiving, and accessibility, aiding in digitizing handwritten notes.	- Existing OCR solutions with more resources and established user bases may challenge the traction of new models. - Variations in individual handwriting styles remain a challenge for achieving high accuracy, particularly in cursive writing. - The fast evolution of deep learning techniques may render current models outdated, necessitating ongoing research to maintain competitiveness.
15	Offline Handwritten Text Recognition Using Deep Learning: A Review	- Leveraging CNNs and RNNs, current OHTR systems achieve competitive sometimes human-level accuracy. - Deep learning architectures especially CNNs, enable efficient, automatic feature extraction reducing dependency on prior knowledge. - Advances in segmentation-free approaches facilitate recognition in complex scenarios handling overlapping text without explicit segmentation.	- RNNs and complex models require extensive resources and time limiting their practicality for many applications. - Deep learning models rely on large, labeled datasets which can be hard to source particularly for niche handwriting styles. - Segmentation-based methods can experience error accumulation impacting overall recognition accuracy.	- Growing interest in weakly supervised methods promises performance gains with minimal labeled data enhancing accessibility. - Combining CNNs and RNNs with techniques like attention mechanisms offers potential for improved recognition accuracy and efficiency. - Rising demand for OHTR in fields like historical document processing presents opportunities to develop industry specific solutions.	- Continuous advancements in AI risk making current OHTR methods outdated if they don't adapt quickly. - High variability in handwriting styles challenges model generalization, especially in diverse applications. - Emerging techniques, such as GANs and innovative hybrid models, introduce new competition, affecting the adoption of traditional deep learning approaches.