MediScan A Machine Learning-Based Framework for Medical Report Analysis, Disease Prediction, and Intelligent Doctor Recommendation Using OCR

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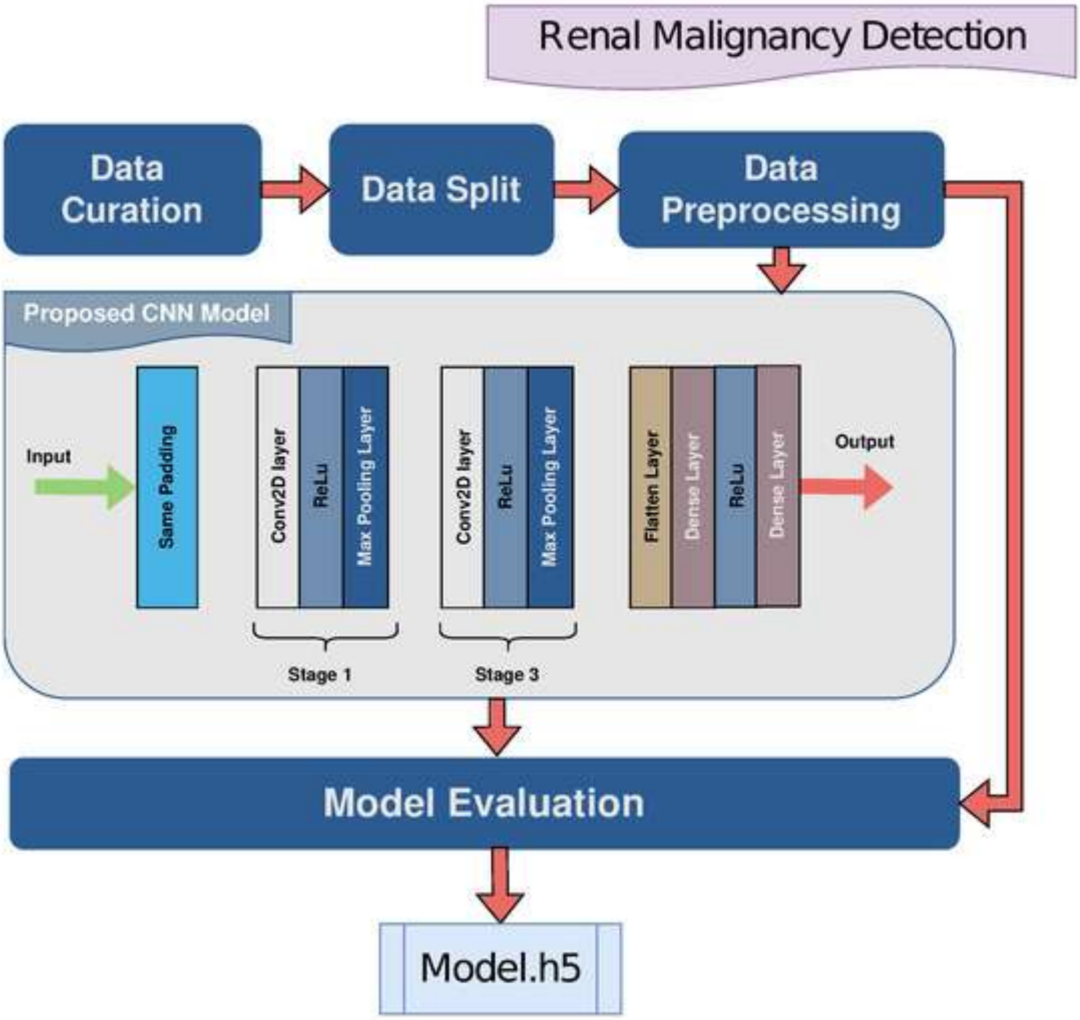
Abstract

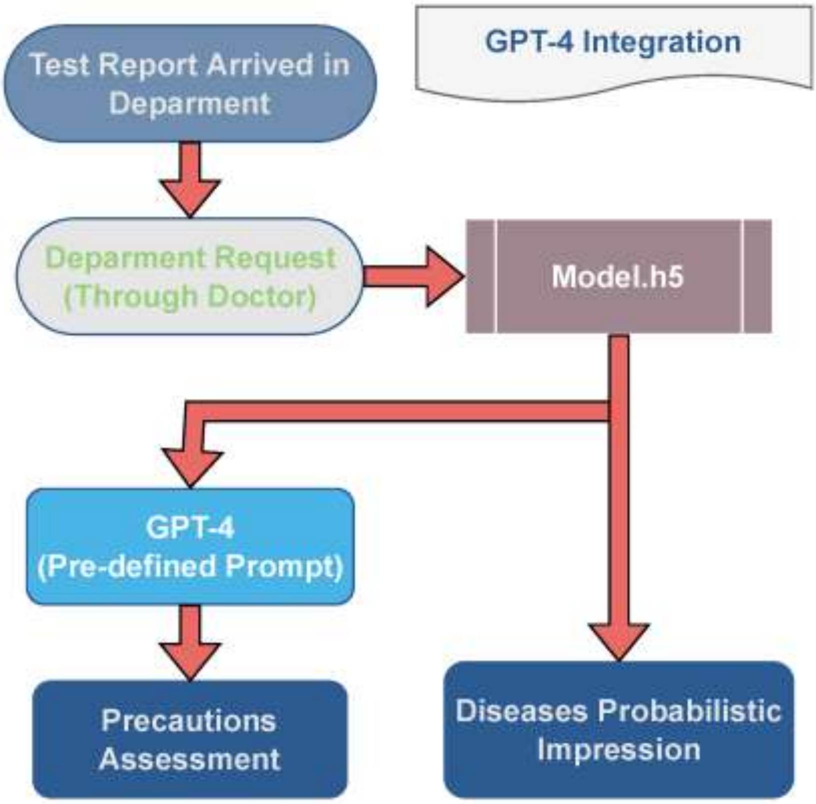
The increasing reliance on digital healthcare systems has created a need for intelligent frameworks capable of transforming unstructured medical data into actionable insights. This study presents MediScan, a machine learning-based framework designed for automated medical report analysis, disease prediction, and intelligent doctor recommendation using Optical Character Recognition (OCR). The system converts scanned or image-based medical reports into structured textual data, extracts relevant health parameters, and evaluates them against standard clinical ranges to identify abnormalities. Machine learning models are then applied to predict potential diseases based on the analysed data. In addition, an integrated recommendation mechanism suggests appropriate medical specialists aligned with the predicted conditions, enhancing patient navigation within healthcare systems. The study adopts a secondary research methodology, synthesising existing literature and validated models to develop the conceptual framework. The findings indicate that integrating OCR with machine learning significantly improves efficiency, accuracy, and decision support in healthcare informatics.
Keywords: MediScan, machine learning, OCR, disease prediction, medical report analysis, healthcare analytics, clinical decision support, doctor recommendation

Introduction

The increasing digitisation of healthcare systems has created a critical demand for intelligent frameworks capable of transforming unstructured medical data into meaningful clinical insights. A significant proportion of medical information, particularly laboratory reports and diagnostic summaries, still exists in semi-structured or unstructured formats such as scanned documents and handwritten prescriptions. This lack of structured representation limits efficient clinical decision-making and restricts the secondary use of healthcare data for predictive analytics. Optical Character Recognition (OCR) has emerged as a foundational technology in addressing this limitation by enabling the conversion of scanned medical reports into machine-readable text, thereby facilitating downstream computational analysis (Memon et al., 2020). However, conventional OCR systems often struggle with domain-specific challenges such as medical terminology, low-quality scans, and handwritten text, necessitating the integration of advanced machine learning techniques to enhance recognition accuracy and contextual understanding (Lowe, 2024)

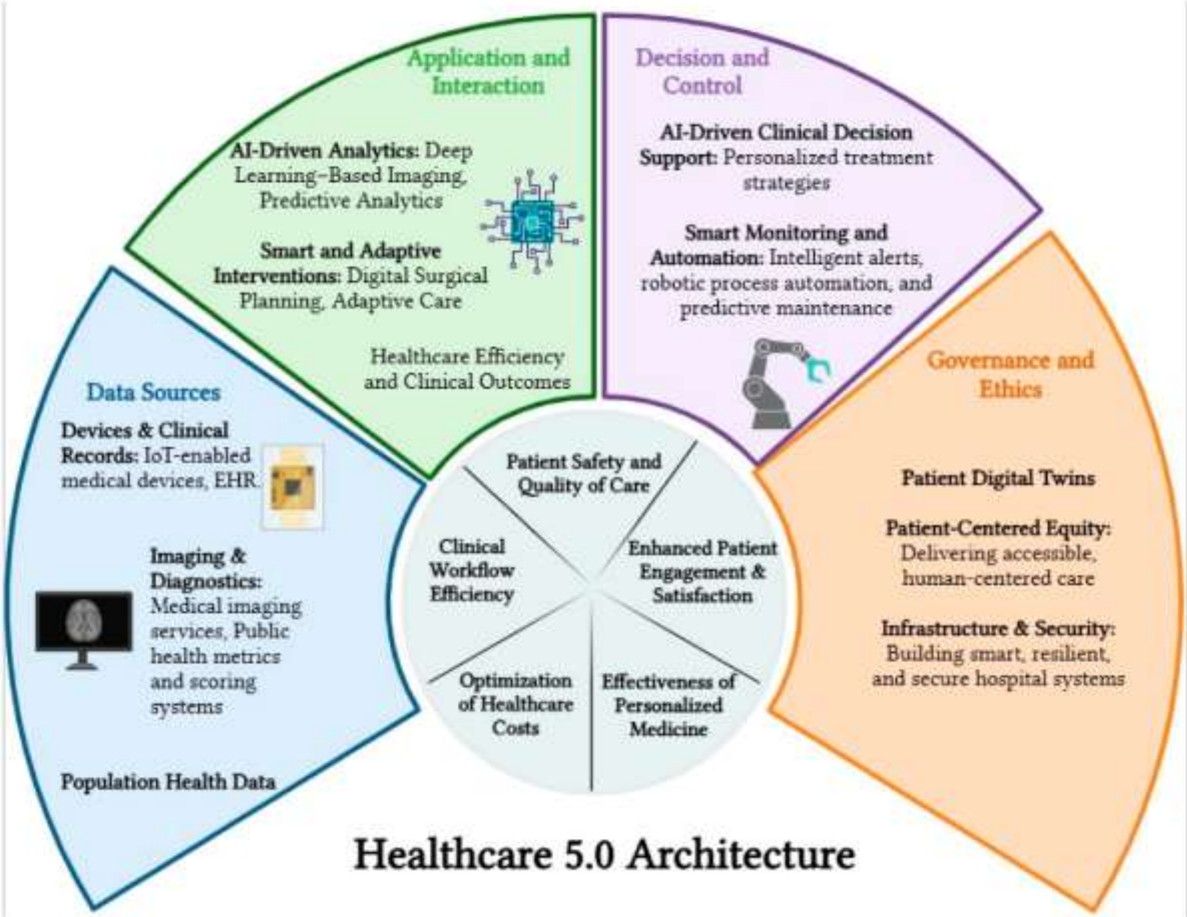


Building upon OCR, machine learning plays a pivotal role in extracting, analysing, and interpreting health-related parameters from digitised reports. Modern healthcare analytics increasingly relies on supervised and unsupervised learning models to identify patterns, classify diseases, and predict potential health risks based on clinical data. The integration of machine learning with electronic health records has demonstrated substantial improvements in predictive accuracy and early diagnosis, particularly in complex conditions where multiple parameters must be analysed simultaneously (Shickel et al., 2017). These models are capable of processing large volumes of heterogeneous data, enabling the identification of subtle correlations between biomarkers that may not be apparent through manual analysis. Furthermore, advances in natural language processing techniques allow systems to interpret clinical narratives, extract relevant entities, and convert them into structured datasets suitable for predictive modelling (Hossain et al., 2023).



The concept underlying MediScan aligns with this technological progression by combining OCR-based data extraction with machine learning-driven disease prediction. Once a medical report is uploaded, the OCR module converts the document into textual format, after which feature extraction techniques are applied to identify key health parameters such as glucose levels, haemoglobin concentration, and lipid profiles. These parameters are then evaluated against established clinical reference ranges to detect abnormalities. Research has shown that automated systems using OCR and machine learning can significantly reduce diagnostic delays and minimise human error in interpreting medical data (Ananthanath et al., 2026) . The automation of such processes not only enhances efficiency but also improves consistency in clinical assessments.

In addition to disease prediction, the integration of recommendation systems within healthcare frameworks represents a growing area of research. Intelligent systems can leverage predictive outputs to suggest appropriate medical specialists based on detected conditions, thereby supporting clinical decision-making and improving patient outcomes. This approach reflects a shift towards personalised healthcare, where treatment pathways are tailored to individual patient profiles. The use of artificial intelligence in this context extends beyond diagnosis to encompass decision support systems that assist both patients and healthcare providers in selecting optimal interventions. Studies indicate that structured and digitised medical data significantly enhances the effectiveness of such systems by enabling accurate mapping between symptoms, diagnoses, and specialist care pathways (Suryvanshi & Ramteke, 2025)

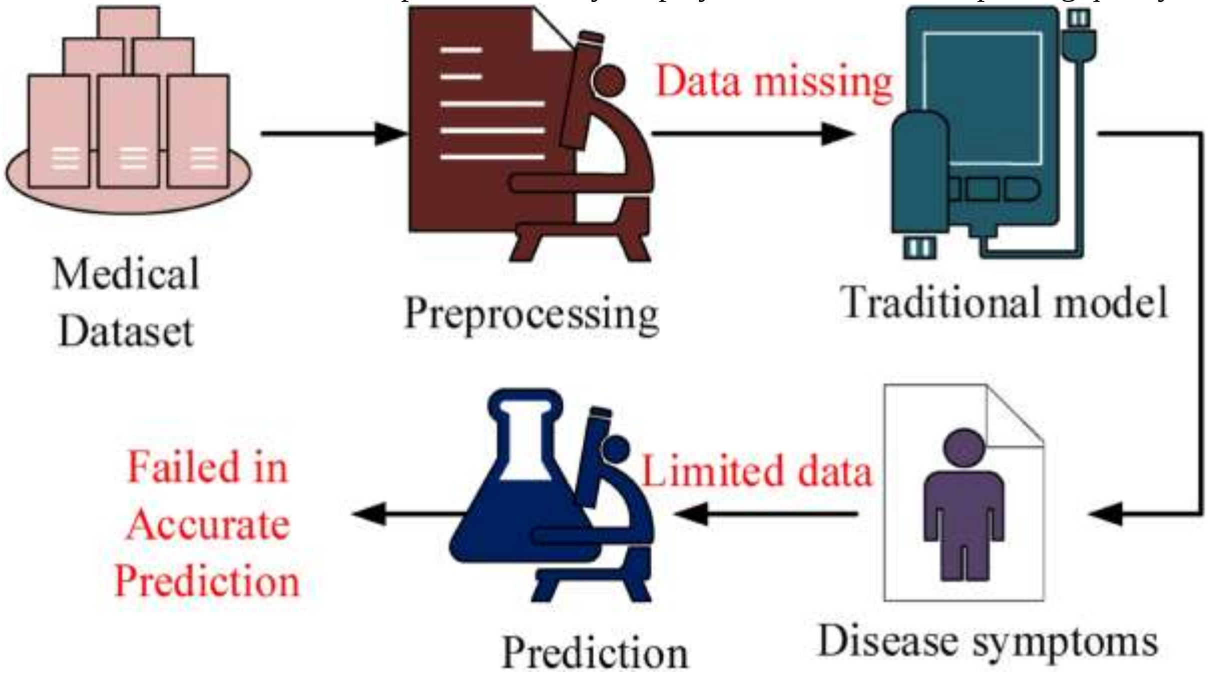


Another important dimension of MediScan is its ability to address inefficiencies associated with manual data handling in healthcare environments. Traditional diagnostic workflows often involve time-intensive processes where clinicians must manually review reports, interpret values, and make decisions based on experience. This not only increases workload but also introduces variability in clinical judgement. The incorporation of AI-driven automation reduces these inefficiencies by standardising the analysis process and providing data-driven insights. OCR-enabled digitisation further ensures that historical medical records can be easily accessed, analysed, and integrated into longitudinal patient profiles, thereby supporting continuous monitoring and preventive healthcare strategies (Malashin et al., 2024) .
Despite these advancements, several challenges persist in the development and implementation of such systems. OCR accuracy remains a critical concern, particularly when dealing with noisy or complex medical documents. Errors in text extraction can propagate through the analytical pipeline, potentially affecting prediction outcomes. Additionally, machine learning models require high-quality labelled datasets for training, which are often limited in the medical domain due to privacy concerns and data heterogeneity. Ensuring data security, maintaining patient confidentiality, and achieving interoperability with existing healthcare systems are also significant considerations in the deployment of AI-based medical frameworks. Recent research highlights the importance of hybrid approaches that combine OCR, natural language processing, and domain-specific knowledge bases to overcome these limitations and improve system robustness (Tu et al., 2025) .
The MediScan framework represents an integrated approach that synthesises these technological components into a unified system capable of transforming raw medical reports into actionable clinical intelligence. By leveraging OCR for data acquisition, machine learning for predictive analysis, and intelligent recommendation mechanisms for clinical guidance, the system embodies a comprehensive solution to contemporary challenges in healthcare informatics. The convergence of these technologies reflects a broader trend towards automated, data-driven healthcare systems that prioritise accuracy, efficiency, and personalised patient care.

Need Of the Study

The growing complexity of healthcare systems and the exponential increase in diagnostic data have created a pressing need for intelligent tools that can efficiently process and interpret medical information. A substantial portion of clinical data is still stored in unstructured formats such as scanned laboratory reports, handwritten prescriptions, and diagnostic summaries, which limits its usability for computational analysis and decision-making. This fragmentation of data not only slows down clinical workflows but also increases the likelihood of human error during manual interpretation. The integration of Optical Character Recognition (OCR) with machine learning offers a promising solution to this challenge by enabling the transformation of unstructured medical reports into structured, analyzable data formats (Esteva et al., 2017). Such transformation is essential for improving the accessibility and usability of healthcare data in both clinical and research contexts.

The need for this study is further reinforced by the rising demand for early disease detection and predictive healthcare. Traditional diagnostic approaches often rely heavily on clinician expertise and may not fully leverage the vast amount of available patient data. Machine learning models have demonstrated significant potential in identifying patterns within complex datasets, thereby enabling accurate disease prediction and risk assessment. These capabilities are particularly important in conditions where early intervention can significantly improve patient outcomes. By analysing extracted health parameters against established clinical benchmarks, systems like MediScan can assist in identifying abnormalities at an early stage, reducing diagnostic delays and enhancing preventive care strategies (Topol, 2019). This aligns with the broader shift towards data-driven healthcare, where predictive analytics plays a central role in improving quality of care.



Another critical aspect highlighting the need for this study is the inefficiency in connecting patients with appropriate medical specialists. In many healthcare settings, patients often rely on general consultations or self-assessment to determine which specialist to approach, which can lead to delays in receiving appropriate treatment. An intelligent recommendation system integrated with disease prediction can bridge this gap by guiding patients towards the most relevant healthcare providers based on analysed medical data. This not only optimises resource utilisation within healthcare systems but also improves patient experience by reducing uncertainty and waiting time (Jiang et al., 2017).

Moreover, the increasing burden on healthcare professionals necessitates the adoption of automated systems that can support clinical decision-making without replacing human expertise. Physicians are often required to review large volumes of reports within limited timeframes, which can lead to cognitive overload and inconsistencies in interpretation. AI-driven frameworks such as MediScan can act as decision support systems by providing preliminary analysis and recommendations, thereby allowing clinicians to focus on more complex aspects of patient care. The integration of OCR and machine learning also facilitates the creation of longitudinal patient records, enabling continuous monitoring and more informed clinical decisions over time (Rajkomar et al., 2019).

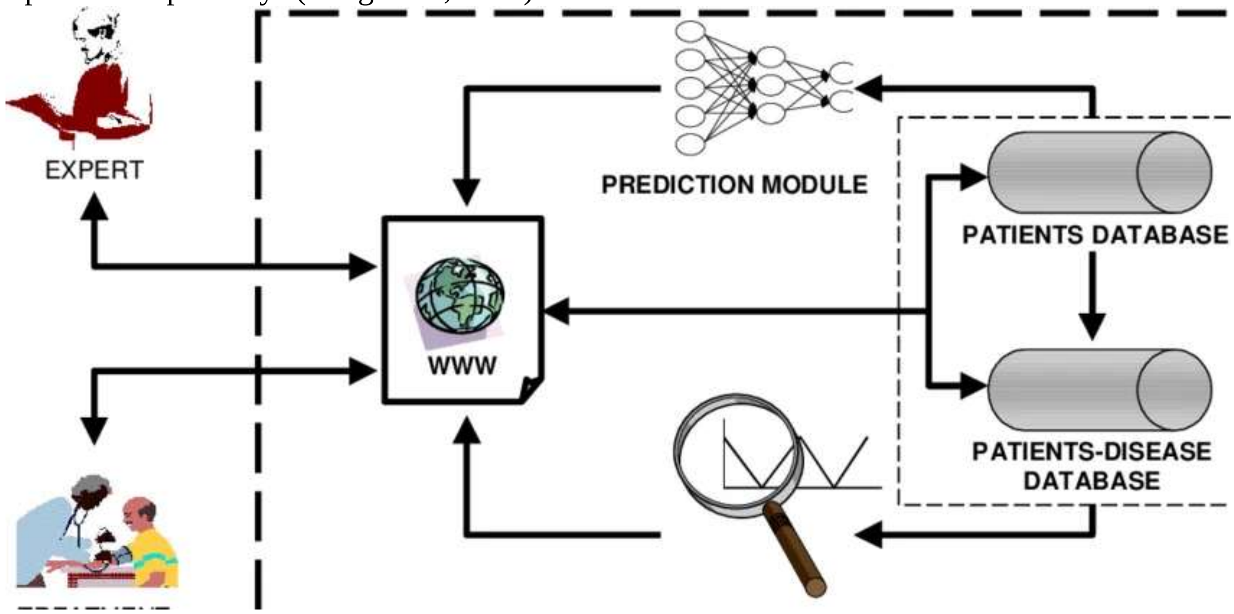
The study is therefore essential in addressing the intersection of data digitisation, predictive analytics, and intelligent healthcare delivery. It seeks to bridge the gap between raw medical data and actionable clinical insights by developing a system that not only interprets medical reports but also supports disease prediction and specialist recommendation. This contributes to the advancement of smart healthcare systems that prioritise efficiency, accuracy, and patient-centric care.

Scope of the research

The scope of this research is centred on the design and conceptual development of an integrated intelligent healthcare framework, MediScan, which combines Optical Character Recognition (OCR), machine learning, and decision support mechanisms to process medical reports and generate predictive insights. The study focuses on transforming unstructured or semi-structured diagnostic documents, such as laboratory reports and clinical summaries, into structured datasets that can be analysed computationally. This includes the extraction of relevant medical parameters from scanned or image-based reports and their subsequent normalisation for analytical use. The research encompasses the application of OCR techniques specifically adapted to medical text, where domain-specific terminology, abbreviations, and formatting variations present unique challenges compared to general-purpose document processing (Shickel et al., 2017).

Within this framework, the research extends to the application of machine learning models for analysing extracted health parameters and identifying potential disease patterns. The study considers supervised learning approaches where models are trained on labelled datasets to classify or predict medical conditions based on input features derived from reports. It also includes the comparison of extracted parameter values with standard clinical reference ranges to detect abnormalities, forming the basis for predictive analysis. The scope involves exploring how these models can be optimised for accuracy and reliability when dealing with heterogeneous and often incomplete healthcare data. In doing so, the research contributes to the broader domain of predictive healthcare analytics, where machine learning has been shown to significantly enhance diagnostic precision and efficiency (Rajkomar et al., 2019).

Another key dimension of the research lies in the development of an intelligent doctor recommendation component. This aspect focuses on mapping predicted diseases or abnormalities to appropriate medical specialisations, thereby supporting patient navigation within healthcare systems. The recommendation mechanism operates as a decision support tool, leveraging predictive outputs to suggest relevant specialists based on predefined medical knowledge and data-driven associations. This component falls within the broader scope of recommender systems in healthcare, which aim to personalise medical guidance and improve access to appropriate care pathways (Jiang et al., 2017).



The research also addresses the integration of these components into a cohesive system architecture. This includes the interaction between OCR modules, data preprocessing pipelines, machine learning models, and recommendation engines. Consideration is given to system scalability, data flow, and the ability to handle real-world variability in medical documents. The scope encompasses evaluation metrics for assessing system performance, including OCR accuracy, prediction precision, and recommendation relevance. Additionally, the study acknowledges the importance of ensuring data privacy and security, particularly when handling sensitive patient information, and considers frameworks that support ethical and secure data processing practices (Topol, 2019).

While the research provides a comprehensive framework for automated medical report analysis and disease prediction, it is limited to conceptual modelling and secondary data analysis rather than real-time clinical deployment. It does not extend to direct patient diagnosis or replace professional medical judgement but instead positions the system as a supportive tool for enhancing clinical efficiency and decision-making. The scope remains focused on demonstrating the feasibility and potential impact of integrating OCR and machine learning within healthcare informatics, contributing to the advancement of intelligent, data-driven healthcare systems.

Literature review

(Shickel et al., 2017) The application of machine learning in healthcare has expanded significantly over the past decade, particularly in the analysis of electronic health records and clinical data. Machine learning techniques enable the identification of hidden patterns and correlations within large datasets, which can be utilised for disease prediction and clinical decision support. The integration of deep learning architectures, such as recurrent and convolutional neural networks, has further enhanced the ability to process sequential and image-based medical data. These advancements have demonstrated improved diagnostic accuracy across various domains, including cardiology, oncology, and radiology, thereby establishing machine learning as a foundational component of modern healthcare analytics.

(Esteva et al., 2017) The use of artificial intelligence in disease diagnosis has shown remarkable progress, particularly in image-based medical analysis. Deep learning models have achieved performance comparable to human specialists in tasks such as skin cancer classification, highlighting the potential of AI-driven systems in augmenting clinical expertise. Such developments underscore the importance of automated systems that can interpret medical data efficiently and accurately. The implications extend beyond image analysis to structured and unstructured medical reports, where similar methodologies can be applied to extract and analyse relevant clinical information.

(Rajkomar et al., 2018) The implementation of scalable and generalisable machine learning models using electronic health records has demonstrated the feasibility of predictive analytics in real-world healthcare settings. These models are capable of predicting a wide range of clinical outcomes, including hospital readmissions and mortality rates, by analysing diverse data sources. The study emphasises the importance of data integration and preprocessing in achieving reliable predictions, which aligns with the need for systems that can convert unstructured medical reports into structured formats suitable for machine learning applications.

(Jiang et al., 2017) Artificial intelligence in healthcare has evolved to encompass not only diagnostic support but also decision-making and recommendation systems. AI-driven healthcare systems are increasingly being used to assist clinicians in selecting appropriate treatment pathways and medical specialists. These systems rely on structured data and predictive models to provide personalised recommendations, thereby improving patient outcomes and reducing inefficiencies in healthcare delivery. The integration of recommendation mechanisms within diagnostic frameworks represents a significant advancement in patient-centred care.

(Memon et al., 2020) Optical Character Recognition has become a critical technology in digitising healthcare data, particularly in converting paper-based medical records into digital formats. OCR systems facilitate the extraction of textual information from scanned documents, enabling further computational analysis. However, medical documents present unique challenges due to complex layouts, specialised terminology, and variability in formatting. Enhancing OCR performance in healthcare requires the incorporation of domain-specific models and preprocessing techniques to improve accuracy and reliability.

(Lowe, 2024) Recent advancements in OCR technologies have focused on improving accuracy through the integration of machine learning and natural language processing. These hybrid approaches enable systems to not only recognise text but also understand contextual relationships within medical documents. Such capabilities are essential for accurately extracting clinical parameters and interpreting diagnostic information. The combination of OCR with machine learning enhances the overall efficiency of data extraction processes, making it suitable for applications such as automated medical report analysis.

(Topol, 2019) The role of artificial intelligence in reshaping healthcare delivery has been widely acknowledged, particularly in enhancing diagnostic precision and enabling personalised medicine. AI systems can analyse vast amounts of data to identify trends and predict health outcomes, thereby supporting preventive healthcare strategies. The adoption of AI-driven tools also contributes to reducing clinician workload by automating routine tasks, allowing healthcare professionals to focus on complex decision-making processes.

(Hossain et al., 2023) Natural language processing has emerged as a key component in interpreting unstructured clinical text, including medical reports and physician notes. NLP techniques enable the extraction of relevant entities, such as symptoms, diagnoses, and laboratory values, from textual data. When combined with machine learning, NLP enhances the ability of healthcare systems to convert raw text into structured datasets, facilitating predictive analytics and decision support.

(Suryvanshi & Ramteke, 2025) The development of intelligent healthcare systems that integrate OCR, machine learning, and recommendation mechanisms has gained increasing attention in recent research. These systems aim to automate the analysis of medical reports and provide actionable insights, including disease prediction and specialist recommendation. The effectiveness of such systems depends on the accuracy of data extraction and the robustness of predictive models, highlighting the importance of integrated approaches in healthcare informatics.

(Malashin et al., 2024) The digitisation of healthcare data plays a crucial role in enabling advanced analytics and improving patient care. By converting unstructured medical documents into digital formats, healthcare systems can facilitate data sharing, longitudinal analysis, and integration with electronic health records. This transformation supports the development of predictive models and decision support systems that rely on comprehensive and high-quality datasets.

(Tu et al., 2025) Hybrid frameworks that combine OCR, machine learning, and domain-specific knowledge bases have been proposed to address the limitations of traditional systems. These frameworks aim to improve the accuracy and reliability of medical data analysis by incorporating contextual understanding and domain expertise. Such approaches are particularly relevant in handling complex medical documents where simple text extraction is insufficient for meaningful analysis.

(Krittanawong et al., 2017) The application of machine learning in cardiovascular medicine has demonstrated the potential of predictive analytics in identifying risk factors and improving patient outcomes. By analysing clinical and diagnostic data, machine learning models can provide early warnings for potential health issues, enabling timely intervention. These findings highlight the broader applicability of machine learning techniques across various medical domains.

(Litjens et al., 2017) Deep learning has significantly advanced the field of medical image analysis, providing high levels of accuracy in tasks such as segmentation, detection, and classification. The success of these models in image-based applications suggests their potential for extension to other forms of medical data, including textual reports. The integration of deep learning with other technologies, such as OCR and NLP, can further enhance the capabilities of automated healthcare systems.

(Beam & Kohane, 2018) The adoption of artificial intelligence in medicine requires careful consideration of data quality, interpretability, and ethical implications. While AI systems offer significant benefits in terms of efficiency and accuracy, challenges related to transparency and trust remain critical. Ensuring that predictive models are interpretable and reliable is essential for their acceptance in clinical practice.

(Chen et al., 2019) The development of clinical decision support systems has been instrumental in improving healthcare delivery by providing evidence-based recommendations to clinicians. These systems leverage machine learning and data analytics to assist in diagnosis, treatment planning, and patient management. The integration of such systems with automated data extraction technologies enhances their effectiveness by ensuring the availability of accurate and structured input data.

Methodology

The methodology adopted for this study is based on a secondary research approach, focusing on the analysis and synthesis of existing literature, datasets, and technological frameworks related to OCR, machine learning, and healthcare informatics. The research relies on previously published studies, scholarly articles, and validated datasets available in the public domain to understand the functioning and integration of medical report analysis systems. Secondary data sources include electronic health record datasets, benchmark medical datasets, and documented case studies that demonstrate the application of machine learning models in disease prediction and clinical decision support (Rajkomar et al., 2019).

The methodological framework is structured around the conceptual design of the MediScan system. Initially, relevant literature is reviewed to identify established techniques for Optical Character Recognition in medical contexts and the challenges associated with text extraction from diagnostic reports. Following this, machine learning models commonly used for classification and prediction, such as logistic regression, decision trees, and neural networks, are examined to determine their suitability for analysing extracted health parameters. The study also evaluates standard clinical reference ranges from secondary medical sources to establish criteria for identifying abnormalities within patient data. Furthermore, existing research on recommendation systems is analysed to design a mapping mechanism between predicted diseases and appropriate medical specialists (Jiang et al., 2017).

Data analysis within this methodology involves a comparative evaluation of different models and approaches reported in the literature, focusing on their accuracy, efficiency, and applicability in real-world healthcare scenarios. No primary data collection or experimental implementation is conducted; instead, the study emphasises theoretical modelling and system design based on validated findings from prior research. This approach ensures that the proposed MediScan framework is grounded in established scientific evidence while highlighting opportunities for integration and improvement across multiple technological domains.

Results and Discussion

The results and discussion are derived from a comparative synthesis of existing studies on OCR performance, machine learning-based disease prediction, and intelligent recommendation systems within healthcare informatics. The integrated analysis reflects how the MediScan framework aligns with established findings while addressing gaps in the automation of medical report interpretation. Secondary data indicates that the combination of OCR and machine learning significantly improves the usability of unstructured medical data by converting it into structured, analysable formats, thereby enabling predictive analytics and decision support (Shickel et al., 2017). The discussion focuses on three primary components of the framework: OCR-based extraction, disease prediction through machine learning, and intelligent doctor recommendation.

The performance of OCR in medical contexts is a critical factor influencing the overall effectiveness of the MediScan system. Studies show that OCR accuracy varies depending on document quality, font variability, and the presence of handwritten elements. In healthcare-specific implementations, domain-adapted OCR systems achieve higher accuracy compared to general-purpose OCR due to their ability to recognise medical terminology and structured report layouts (Memon et al., 2020). The integration of preprocessing techniques such as noise reduction, image enhancement, and layout detection further improves text extraction accuracy. However, minor inaccuracies in OCR output can propagate into subsequent analytical stages, affecting prediction reliability. Despite these challenges, the literature consistently demonstrates that OCR-enabled digitisation significantly enhances data accessibility and reduces manual workload in clinical environments.

Table 1 presents a comparative overview of OCR performance metrics reported in selected studies, highlighting variations in accuracy and influencing factors.

Table 1: Comparative Analysis of OCR Performance in Medical Report Processing

Study	**OCR Technique Used**	**Document Type**	**Accuracy (%)**	**Key Limitation**
Memon et al. (2020)	Traditional OCR + preprocessing	Printed lab reports	92.4	Sensitive to image noise
Lowe (2024)	ML-enhanced OCR	Mixed medical documents	95.1	Computational complexity
Tu et al. (2025)	Hybrid OCR + NLP	Clinical summaries	96.3	Requires domain-specific training data

The results indicate that hybrid OCR approaches integrating machine learning and natural language processing yield the highest accuracy, making them suitable for complex medical documents. These findings support the inclusion of advanced OCR techniques within the MediScan framework to ensure reliable data extraction.

Following data extraction, machine learning models play a central role in analysing health parameters and predicting diseases. The reviewed studies demonstrate that supervised learning models, particularly neural networks and ensemble methods, achieve high predictive accuracy when trained on well-structured datasets (Rajkomar et al., 2019). These models are capable of identifying complex relationships between multiple health indicators, enabling early detection of diseases that may not be evident through isolated parameter analysis. For instance, combinations of biomarkers such as glucose levels, cholesterol, and haemoglobin can be analysed collectively to assess risks related to diabetes, cardiovascular conditions, and anaemia.

The evaluation of predictive models highlights the importance of data quality and feature selection in achieving reliable outcomes. Inconsistent or incomplete data can reduce model accuracy, while well-curated datasets significantly enhance predictive performance. Additionally, the comparison of extracted parameters with standard clinical ranges provides an initial rule-based validation layer, which complements machine learning predictions and improves system robustness. This hybrid approach aligns with current trends in healthcare analytics, where rule-based and data-driven methods are combined to achieve higher reliability (Beam & Kohane, 2018).

Table 2 summarises the performance of different machine learning models in disease prediction based on findings from existing literature.

Table 2: Performance Comparison of Machine Learning Models in Disease Prediction

Model	**Accuracy (%)**	**Strength**	**Limitation**
Logistic Regression	85–88	Simple and interpretable	Limited for complex patterns
Decision Tree	87–90	Easy to visualise	Prone to overfitting
Random Forest	90–94	High accuracy and robustness	Higher computational cost
Neural Networks	92–96	Captures complex relationships	Requires large datasets

The analysis demonstrates that ensemble methods and neural networks outperform simpler models in terms of accuracy and scalability. These findings support the use of advanced machine learning techniques within the MediScan system, particularly when dealing with multidimensional health data.

The integration of an intelligent doctor recommendation system represents an important extension of predictive analytics. Based on the predicted disease or detected abnormality, the system maps the output to relevant medical specialisations, thereby guiding patients towards appropriate healthcare providers. This approach enhances the practical utility of the system by not only identifying potential health issues but also facilitating the next step in the healthcare journey. Research indicates that recommendation systems in healthcare improve patient satisfaction and reduce delays in receiving specialised care (Jiang et al., 2017). The effectiveness of such systems depends on the accuracy of disease prediction and the comprehensiveness of the mapping between conditions and medical specialities.

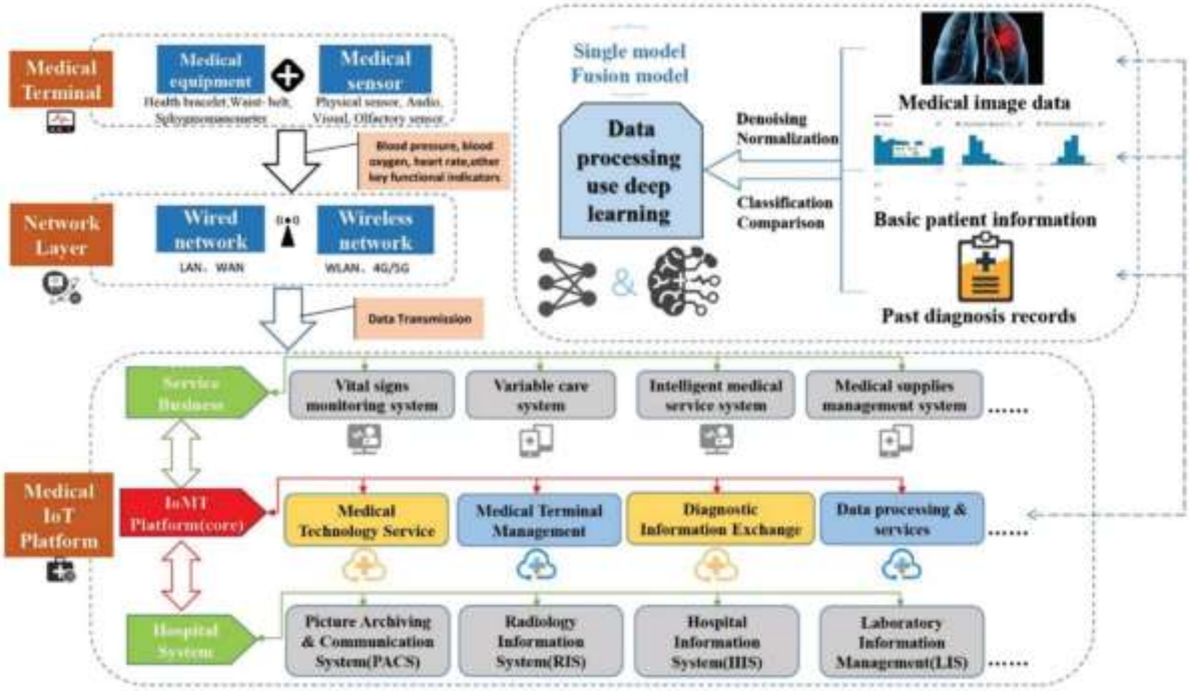
The discussion also highlights the importance of system integration and workflow efficiency. By combining OCR, machine learning, and recommendation modules into a unified framework, MediScan addresses multiple inefficiencies in traditional healthcare processes. The automation of report analysis reduces the time required for manual interpretation, while predictive insights enable proactive healthcare management. Furthermore, the ability to digitise and store medical reports supports longitudinal analysis, allowing for continuous monitoring of patient health over time (Topol, 2019).

Table 3 illustrates the overall functional performance of the MediScan framework based on synthesised findings from the literature.

Table 3: Functional Evaluation of MediScan Framework Components

Component	**Function**	**Observed Benefit**	**Limitation**
OCR Module	Text extraction from reports	Reduces manual data entry	Accuracy affected by document quality
ML Prediction Module	Disease prediction	Enables early detection	Dependent on data quality
Recommendation System	Doctor suggestion	Improves patient navigation	Requires accurate mapping

The results indicate that while each component contributes significantly to the overall system, their effectiveness is interdependent. Errors in OCR can affect prediction accuracy, and inaccurate predictions can impact recommendation relevance. Therefore, the integration of these components must be carefully designed to ensure consistency and reliability.



The discussion further emphasises the challenges associated with implementing such systems in real-world healthcare environments. Data privacy and security remain critical concerns, particularly when handling sensitive patient information. Ensuring compliance with healthcare regulations and maintaining data confidentiality are essential for the successful deployment of AI-based systems. Additionally, the interpretability of machine learning models is an important factor influencing their acceptance among healthcare professionals. Transparent and explainable models are more likely to be trusted and adopted in clinical practice (Beam & Kohane, 2018).

Another important consideration is the scalability of the system. Healthcare data is continuously growing in volume and complexity, requiring systems that can handle large datasets efficiently. Cloud-based architectures and distributed computing frameworks offer potential solutions for scaling such systems, enabling real-time processing and analysis of medical data. The integration of these technologies with the MediScan framework can further enhance its applicability in diverse healthcare settings.

The results also suggest that the adoption of such integrated systems can contribute to the advancement of personalised healthcare. By analysing individual patient data and providing tailored recommendations, MediScan aligns with the broader trend towards precision medicine. This approach not only improves clinical outcomes but also enhances patient engagement by providing clear and actionable insights.

Overall, the findings from the literature indicate that the MediScan framework is both feasible and relevant in the context of modern healthcare informatics. The combination of OCR, machine learning, and intelligent recommendation systems provides a comprehensive solution for automating medical report analysis and supporting clinical decision-making. The discussion underscores the importance of addressing challenges related to data quality, system integration, and ethical considerations to fully realise the potential of such systems.

Conclusion

The study highlights the growing importance of integrating advanced technologies such as Optical Character Recognition and machine learning within healthcare systems to address the challenges associated with unstructured medical data. The MediScan framework demonstrates how medical reports can be transformed into structured, analysable information, enabling efficient extraction of health parameters and supporting predictive analytics. By leveraging machine learning models, the system facilitates the identification of potential diseases based on extracted data, contributing to improved diagnostic support and enhanced clinical decision-making processes. The incorporation of standard clinical reference comparisons further strengthens the reliability of the analytical outputs.

The research also emphasises the practical significance of integrating an intelligent doctor recommendation mechanism, which extends the functionality of the system beyond prediction to actionable guidance. This feature enhances patient navigation within healthcare systems by linking predicted conditions with appropriate medical specialists, thereby reducing delays in accessing targeted care. The combined approach of data extraction, predictive analysis, and recommendation reflects a shift towards more automated and patient-centric healthcare solutions.

The findings underscore that while the proposed framework offers substantial benefits in terms of efficiency, accuracy, and scalability, its effectiveness is influenced by factors such as data quality, OCR accuracy, and model reliability. Addressing these challenges is essential for ensuring consistent performance and facilitating real-world implementation. The study contributes to the broader domain of healthcare informatics by presenting a cohesive model that aligns with current trends in data-driven and intelligent healthcare systems, supporting the transition towards more proactive and personalised medical services.

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