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AI-Based Clinical Decision Support Framework for Health Report Visual Analytics

Gajalakshmi N[1], Harishmi R[2], Lishiga T[3]
[1]Assistant Professor, Artificial Intelligence and Data Science, Kamaraj College of Engineering and Technology, Virudhunagar, Tamil Nadu, India.
[2,3]UG - Artificial Intelligence and Data Science, Kamaraj College of Engineering and Technology, Virudhunagar, Tamil Nadu, India.
Emails: *gajalakshmiads@kamarajengg.edu.in[1], harishmiark09@gmail.com[2], lishigat@gmail.com[3]*

Abstract
Healthcare systems generate a large volume of clinical reports containing laboratory results, diagnostic observations, and patient information. These reports are often unstructured and require manual interpretation by clinicians, which can be time-consuming and prone to human error. This paper proposes an AI-based Clinical Decision Support Framework designed to automatically analyze health reports and generate meaningful insights through visual analytics. The proposed system integrates Natural Language Processing (NLP) techniques for extracting clinical entities from medical reports, Random Forest algorithms for disease risk prediction, and open Large Language Models (LLMs) for generating contextual health insights. The framework processes patient reports in multiple formats such as PDF, CSV, and Electronic Health Records (EHR), converts unstructured medical data into structured features, and performs automated health analysis. The extracted results are presented through interactive visual dashboards including charts, trend graphs, and heatmaps to support clinicians in identifying abnormalities and making informed decisions. Experimental evaluation demonstrates that the system improves the efficiency of medical report interpretation and enhances decision support by providing automated insights and predictive analytics. The proposed framework contributes toward intelligent healthcare systems by combining machine learning, NLP, and visual analytics for improved clinical decision-making.
Keywords: *Clinical Decision Support System, Health Report Analysis, Natural Language Processing, Machine Learning, Visual Analytics, Healthcare AI.*

1. Introduction
The rapid growth of digital healthcare systems has resulted in the generation of large volumes of electronic medical records and clinical reports. These reports contain valuable information such as laboratory test results, diagnostic observations, and patient medical history. However, most health reports exist in unstructured or semi-structured formats, making manual interpretation necessary. This process can be time-consuming and may lead to errors or delays in diagnosis. Therefore, intelligent systems are required to automatically analyze health reports and assist clinicians in interpreting complex medical information. Clinical Decision Support Systems (CDSS) have been developed to support healthcare professionals by providing data-driven insights and recommendations [3]. With the advancement of Artificial Intelligence (AI), machine learning techniques are increasingly being used to analyze healthcare data and identify potential disease risks. Natural Language Processing (NLP) methods enable the extraction of important clinical information from unstructured medical reports, while machine learning models help in identifying patterns and predicting health conditions (Reyes-Ortiz et al., 2024; Linhares et al., 2022). Despite these developments, many existing systems lack the ability to combine automated text extraction, predictive analytics, and visual interpretation of health data. Visual analytics tools can transform complex medical data into graphical representations such as charts and dashboards, [7] allowing healthcare professionals to easily understand patient health trends and identify abnormalities. This research proposes an AI-Based Clinical Decision Support Framework for Health

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Report Visual Analytics. The proposed system integrates Natural Language Processing for extracting clinical information, Random Forest algorithms for disease risk prediction, and open Large Language [2] Models for generating contextual insights. The analyzed results are presented through visual dashboards to support clinicians in making informed decisions and improving healthcare data interpretation.

1.1. Data Extraction from Clinical Reports

Clinical reports often contain important medical information in textual format, including laboratory results, vital signs, and diagnostic observations. Natural Language Processing techniques can automatically extract these clinical entities and convert them into structured data. This process helps in reducing manual effort and improves the efficiency of analyzing medical documents.

1.2. AI-Based Prediction and Visual Analytics

Machine learning algorithms are used to analyze the extracted health parameters and identify potential health risks. In the proposed system, the Random Forest algorithm is used to perform predictive analysis due to its effectiveness in handling complex healthcare data [11]. The analyzed results are presented through visual dashboards such as graphs and charts, enabling healthcare professionals to easily interpret patient health trends and make better clinical decisions.

2. Method

The proposed AI-based Clinical Decision Support Framework is designed to automatically analyze clinical health reports and generate meaningful insights through machine learning and visual analytics. The methodology consists of several stages including data collection, preprocessing, feature extraction, predictive analysis, and visualization. The overall workflow converts unstructured health reports into structured data and produces interpretable health insights that assist clinicians in decision-making. The framework processes patient health reports in multiple formats such as PDF files, CSV datasets, and Electronic Health Records (EHR). The collected data undergoes preprocessing to remove noise and prepare the information for analysis. Natural Language Processing techniques are then applied to extract key clinical entities from the reports. These extracted features are analyzed using machine learning algorithms to identify potential health risks [8]. Finally, the analyzed results are presented through visual dashboards that help healthcare professionals.

2.1. Data Collection and Preprocessing

The first step in the proposed system involves collecting patient health reports from various sources such as laboratory reports, medical records, and diagnostic summaries [1]. These reports may exist in structured formats like CSV or semi-structured formats such as PDF documents. Since many health reports contain textual information, preprocessing techniques are applied to clean and normalize the data. The preprocessing stage includes text cleaning, removal of irrelevant characters, normalization of medical terms, and formatting of numerical values. In cases where the reports are in image-based PDF format, Optical Character Recognition (OCR) techniques are used to convert the text into machine-readable form. These preprocessing steps ensure that the extracted information is accurate and suitable for further analysis.

2.2. Feature Extraction Using Natural Language Processing

After preprocessing, Natural Language Processing (NLP) techniques are applied to extract relevant medical information from the clinical reports. NLP methods help identify important clinical entities such as laboratory test values, patient vitals, diagnostic observations, and medication details. Techniques such as tokenization, keyword extraction, and named entity recognition are used to identify key health parameters. The extracted data is then converted into structured features that can be used as input for machine learning models. This process allows the system to transform UNSTRUCTURED medical text into meaningful data representations suitable for predictive analysis.

2.3. Health Risk Prediction Using Machine Learning

The structured features obtained from the NLP module are analyzed using machine learning algorithms to identify potential health risks and abnormalities [5]. In this framework, the Random Forest algorithm is used as the primary predictive model due to its robustness and ability to handle high-

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dimensional medical data. Random Forest is an ensemble learning technique that constructs multiple decision trees and combines their outputs to produce accurate predictions. By analyzing different health parameters simultaneously, the model can detect patterns associated with various health conditions and generate risk predictions. The use of this algorithm improves the reliability and accuracy of the decision support system.

2.4. Insight Generation Using Large Language Models

To improve interpretability, the system integrates open Large Language Models (LLMs) that generate contextual explanations from the analyzed data. These models process the extracted clinical information and prediction results to produce human-readable insights. This feature helps clinicians better understand the significance of the results and supports more informed clinical decision-making.

2.5. Visual Analytics and Result Presentation

The final stage of the framework involves presenting the analyzed results through visual analytics. Data visualization techniques such as line charts, bar graphs, and heat maps are used to display patient health trends and abnormal indicators. Interactive dashboards allow clinicians to easily monitor patient health parameters and compare historical data.

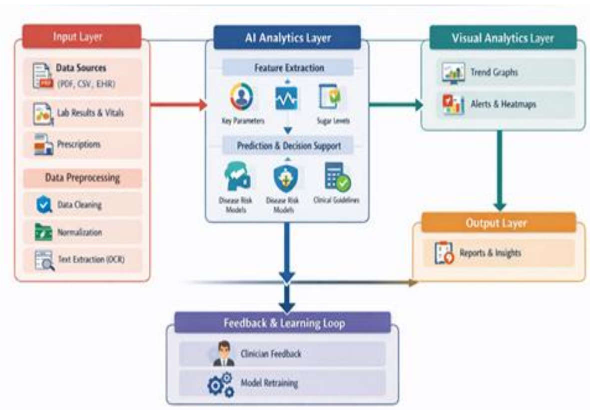

Figure 1 Architecture of AI-Based Clinical Decision Support Framework

The Figure 1 illustrates the architecture of the AI-Based Clinical Decision Support Framework for Health Report Visual Analytics. The system begins with the Input Layer, where patient data such as health reports, lab results, and prescriptions are collected from sources like PDF, CSV, and EHR files [13]. This data undergoes preprocessing steps including data cleaning, normalization, and text extraction using OCR. In the AI Analytics Layer, important clinical features are extracted from the processed data, and machine learning models are used to predict disease risks and support clinical decisions. The analyzed results are then presented in the Visual Analytics Layer through trend graphs, alerts, and heatmaps for easy interpretation. Finally, the Output Layer generates reports and insights for clinicians, while a Feedback and Learning Loop allows clinician feedback to improve the model through retraining and continuous learning.

3. Results and Discussion

3.1. Results

The proposed AI-Based Clinical Decision Support Framework for Health Report Visual Analytics was implemented to analyze clinical health reports and generate meaningful medical insights using Artificial Intelligence techniques. The system was tested using sample health reports containing laboratory results, patient vitals, and prescription information [6]. The framework successfully processed input reports in formats such as PDF and structured datasets, demonstrating its ability to handle different types of healthcare data.

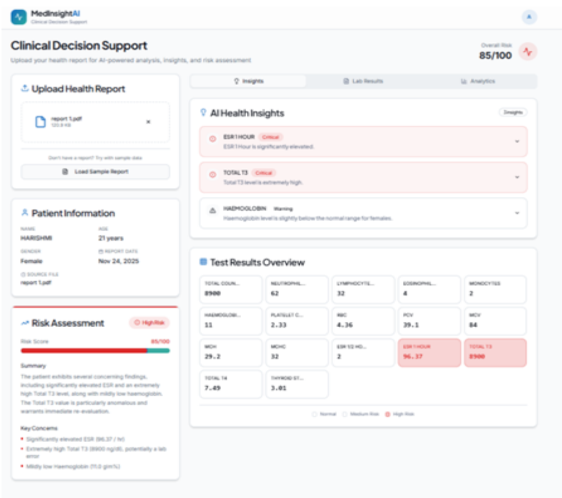

Figure 2 Workflow of Health Report Processing

Figure 2 illustrates the workflow of processing clinical health reports using Natural Language Processing and machine learning techniques. The

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process begins with collecting patient health reports from sources such as PDF files, CSV datasets, or Electronic Health Records. The reports undergo preprocessing steps including data cleaning, normalization, and text extraction. NLP techniques are then applied to extract important clinical features such as laboratory values, vital signs, and diagnostic indicators [4]. These features are analyzed using machine learning algorithms to identify potential health risks. Finally, the analyzed results are presented through visual analytics dashboards to support clinicians in understanding patient health conditions and making informed medical decisions.

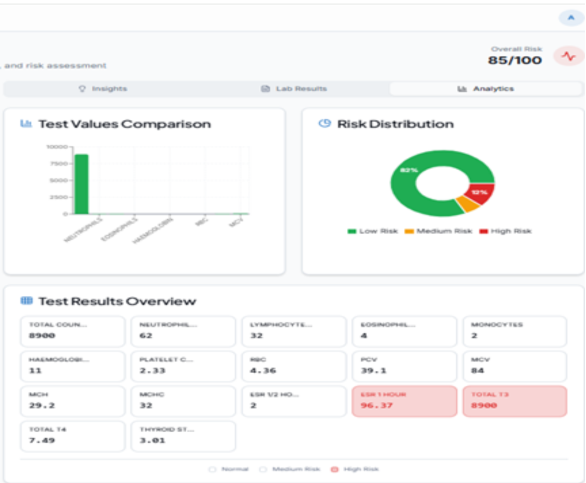

Figure 3 Visual Analytics Dashboard Showing Patient Health Trends

Figure 3 presents the visual analytics dashboard that displays patient health parameters through graphical representations such as charts and trend graphs. The dashboard helps clinicians monitor changes in vital signs and laboratory results over time. By visualizing health data, the system enables quick identification of abnormal values and supports better understanding of patient health conditions for effective clinical decision-making.

Discussion

The proposed AI-Based Clinical Decision Support Framework effectively demonstrates how Artificial Intelligence techniques can improve the analysis of clinical health reports. The system successfully processes health reports from different formats and converts unstructured medical data into structured information through preprocessing and Natural Language Processing techniques. This automation reduces the need for manual interpretation and improves the efficiency of analyzing clinical documents. The extracted health parameters are analyzed using the Random Forest machine learning model [10], which helps identify abnormal patterns and predict potential health risks. The model provides reliable predictions by considering multiple clinical indicators simultaneously. In addition, the integration of visual analytics dashboards allows clinicians to easily observe patient health trends through charts and graphs, improving the interpretability of medical data. Furthermore, the use of open Large Language Models enables the system to generate understandable insights from complex health information. Overall, the proposed framework demonstrates the potential of combining NLP, machine learning, and visualization techniques to support better clinical decision-making and improve healthcare data analysis.

Conclusion

This paper presented an AI-Based Clinical Decision Support Framework for Health Report Visual Analytics that aims to improve the analysis and interpretation of clinical health reports. The proposed system integrates Natural Language Processing, Random Forest machine learning algorithms, and visual analytics techniques [9]to automatically extract important medical information from patient health reports and generate meaningful insights. The framework successfully processes clinical reports from multiple formats, converts unstructured medical data into structured features, and performs predictive analysis to identify potential health risks [12]. The integration of visual dashboards enables healthcare professionals to easily interpret patient health trends and detect abnormal indicators. In addition, the use of open Large Language Models helps generate understandable insights from complex medical data. Overall, the proposed system demonstrates the effectiveness of combining AI techniques with healthcare analytics to support clinical decision-making. The framework can reduce manual effort in analyzing medical reports and assist clinicians in identifying health risks more efficiently. Future work may focus on improving prediction accuracy by using larger healthcare datasets and integrating additional machine learning models to enhance the system's performance in real-world healthcare applications.

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