Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

School of Computer Science and Engineering

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Vandalur – Kelambakkam Road, Chennai – 600127

Programme : BTECH (CSE)

Course : Natural Language Processing (BCSE409L)

Slot : D2 + TD2

Faculty : Vijayaprabakaran K

Title : A HYBRID APPROACH TO MEDICAL REPORT ANALYSIS USING NLP & AI

A HYBRID APPROACH TO MEDICAL REPORT ANALYSIS USING NLP & AI

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Abstract- The report describes the Medical Report Analyser that provide assistance from an AI-based application for the automation of analysis and interpretation of clinical reports' evidence. The system, in PDF or screen capture formats, analyses medical reports and generates diagnostic summaries of key findings clinical impression, as well as an initial list of recommendations in structured outputs.The MRA works in a hybrid setup where the generative language model like Google's Gemini is expected to provide a decent abstract while the deep understanding of medical concepts and terminology has been complemented with BERT. WordNet has been configured within the system, thus giving extra semantic precision and concept understanding by enabling the identification of synonyms as well as its contextual mapping to several medical expressions.Though the intuitive interface built-in Streamlit offers easy engagement and report uploading with the facility of visualising insights. This makes the application demonstrate the cutting-edge capability of natural language processing methodologies and open-sourced lexical utilities in easing the heavy clinical interpretative burden, aiding diagnostic decision-making, and offering access to patients regarding medical knowledge.The paper thus concludes by emphasising the empowering potential of smart frameworks in health informatics regarding pulling information and communication technologies into clinical practice through automation in the field of medical report analysis.

Keywords-MRA, BERT, LLM, WordNet, Streamlit

I. INTRODUCTION

Increased sophistication and amounts of healthcare data have made the deployment of artificial intelligence (AI) methods, such as Natural Language Processing (NLP), unavoidable to enhance clinical decision-making speed and accuracy. Of the hundreds of medical data sources, however, unstructured information like discharge summaries, reports, and handwritten physician notes remain a challenge to automated processing. Manual analysis of these documents is not only time-consuming but also prone to human errors, which puts a premium on intelligent systems that can comprehend and summarise medical language successfully [1][2].

Recent advancements in NLP have introduced powerful models such as BERT (Bidirectional Encoder Representations from Transformers), which excels in capturing contextual semantics of language, making it particularly suitable for deciphering the intricate and domain-specific vocabulary present in medical documents [3][4]. Similarly, lexical databases like WordNet aid in resolving semantic ambiguity by mapping relationships between medical terms, while conversational AI models such as Gemini (Google's Generative AI) enable real-time summarisation and insight generation from raw clinical text [5][6].

The proposed system, Medical Report Analyser, makes use of a combination of these modern NLP tools to extract both image-based and text-based medical reports. With the inclusion of BERT for contextual embedding, WordNet for lexical analysis, and Gemini API for generative summarisation, the system provides succinct and coherent explanations of complex medical information. It also includes an interactive user interface built using Streamlit, making it simple to upload, process, and visualise medical documents by the end-user [7][8].

This study seeks to close the gap between medical NLP theory and clinical practice use by providing an interpretable, scalable, and efficient solution to automating medical report analysis. The research also tackles important issues such as semantic vagueness, contextual sense, and summarisation of unstructured healthcare information, thus making its contribution to the developing domain of AI in digital health systems [9][10].

II. OBJECTIVES

A. Multi-format Report Processing System:

Medical reports are usually going to be available or sent out in a number of different formats such as PDF files, scanned documents, or images of handwritten documents. The system is to take care of both text-based and image-based input forms. It provides features to read text data from a PDF file with the help of libraries like PyPDF2 and manages image files through the OCR as well as AI-based image processing.

B. Utilise BERT for Contextual Text Analysis:

Another key feature of the system will be the use of BERT (Bidirectional Encoder Representations from Transformers), a state-of-the-art deep learning technology developed by Google to deal with NLP. BERT serves the purpose of understanding within the system the sentence context of how words and medical terms are related to each other. This is even more important in medical documents since the meaning of the terms used differs depending on the context. In this way, the analyser is able to render more accurate and subtle interpretation using BERT while working on the case history.

C. Integrate WordNet for Semantic Enhancement:

The embedding of WordNet provides the system with more habitat for semantic enhancement. This makes available all the synonym sets (synsets), antonyms, and relations of words made use of in bridging the terminological gaps, which in this particular case would enable the system to understand that "hypertension" and "high blood pressure" would mean the same thing but framed differently in varying sections of the report. Flexibility in the semantic dimension would translate to better coverage and improved text analysis.

D. Generative Summarisation with AI:

The system also makes use of generative AI (of course, including Google's Gemini model) to produce short readable summaries for end-users, which will definitely help the audience comprehend the medical information easily. The generative model assimilates all analysed pieces of information to create descriptions in natural language, snapshots of significant findings, diagnostic impressions, and possible recommendations. This helps even to read through the most complex document in seconds and get the gist of its message.

E. User-Friendly Interface with Streamlit:

The transformation of data into a usable and accessible format is a goal of this research. In achieving that, the system is deployed with Streamlit, a web application framework for Python that enables the building of interactive user-oriented interfaces. The interface allows users to upload clinical reports and obtain a structured AI-driven output in real time. The platform is developed for inclusive usability such that both healthcare practitioners and patients will get complex medical information in a legible and interpretable format. The platform further integrates responsive data visualisation components to enhance the readability and clinical interpretation of the extracted results.

III. LITERATURE REVIEW

Artificial Intelligence (AI) and Natural Language Processing (NLP) have found increasing applications in the field of medical report analysis, describing how healthcare professionals come to interpret and manage patient information. Such models are able to pull crucial information regarding the diagnoses, treatment recommendations, and findings, thereby improving the efficiency and accuracy of clinical decision-making respectively.

A. Challenges in Medical Report Analysis

There are different challenges encountered during medical report analysis. Medical terms that are dense and ambiguous, acronyms, and polysemous words can have different meanings based upon contextual understanding. Traditional approaches that rely on keywords tend to struggle in determining this subtlety. In contrast, it is exactly this contextual meaning of a word that renders BERT particularly suitable in tackling such difficulties. By enabling bidirectional processing of medical texts, BERT supports the collecting of the entire clinical term context to render a precise and trustworthy interpretation.

B. NLP Techniques Applied in the Research

The research is embedded with a BERT for medical language understanding and proposition to allow proper interpretation of medical terms. The next is WordNet which is extracted for semantic understanding, especially in synonymy and hierarchical relationships within medical terms. From these models, the research can also process and analyse text and image-based medical reports as well as generate actionable insights that can be used to make better decisions in healthcare.

The realisation of the proposed system suitable for a hospital environment. The research aims to assess and validate the absorbed functionalities of systems into a real-life hospital and healthcare setting-centre research to test, evaluate, and validate the functionalities of the system against a hospital and healthcare real-time context.

The P-Diabetes Research was conceived upon the successful completion of the Voice-Based Assistive Application for the Speech-Impaired, thus hoping to close the diabetes prediction gap among populations. The research aims to develop an intelligent solution, whose prototype demonstration will also provide evidence toward the same issue.

PAPER	KEY FINDINGS	RESEARCH GAPS FILLED BY THE PAPER
Huang et al. (2023)	BERT-based clinical knowledge extraction techniques were created for biomedical knowledge graph building and analysis. These models enhance the extraction of structured information from clinical reports.	This research applies BERT to text and image-based medical report analysis, expanding the knowledge extraction to more varied report types.
Rasmy et al. (2021)	BERT-based clinical knowledge extraction techniques were created for biomedical knowledge graph building and analysis. These models enhance the extraction of structured information from clinical reports.	BERT-based clinical knowledge extraction techniques were created for biomedical knowledge graph building and analysis. These models enhance the extraction of structured information from clinical reports.
Lee et al. (2022)	This research paper proposes a model for medical report analysis specialty prediction from recorded text based on a domain-specific pre-trained BERT, enhancing routing in healthcare.	This work builds upon this domain-specific pre-trained BERT..by aiming to summarise and analyse complete medical reports, deriving actionable insights instead of routing based on specialties.
Jung et al. (2024)	A BERT-based NLP model was created to identify inpatient falls from multidisciplinary progress notes, enhancing patient safety.	This research extends this BERT-based model by extending the approach to a wider range of medical reports, allowing AI-based analysis for other conditions beyond falls.
Banerjee et al. (2021)	BI-RADS BERT was used for radiology report interpretation, with the ability to segment and analyse sections for more accurate findings.	The present research incorporates BERT-based NLP analysis for image as well as text-based reports, extending its use to non-radiology medical reports as well.
Smit et al. (2020)	CheXbert, an application regarding the BERT-based system, identifies and annotates radiology reports with high accuracy automatically.	This research modifies BERT to be well applicable for general analysis of medical reports beyond..radiology, adding in text summarisation and image analysis.
Li et al. (2020)	BERT-based analysing models were utilised to make clinical medical diagnoses significant to health histories with better performance compared to the conventional approach.	This research applies BERT for comprehensive analysis and summarisation, filling the gap in providing not only predictions but also clinical insights from complex medical reports.
Feng et al. (2024)	BERT was implemented for medical information processing with approaches like contrastive learning and integration with ChatGPT to improve semantic understanding.	The integration of WordNet and BERT in this research addresses the need for accurate, contextually aware, and semantically enriched medical report interpretation.
Liu et al. (2022)	Deep learning methods integrating BERT and WordNet have demonstrated great im provement in medical text classification tasks.	The current research adopts BERT and WordNet for both classification and generative summarisation, facilitating a more holistic medical report analysis.

Table I: Comparison of Medical Report Analysis Models

Caruana et al. (2020) and Choudhury et al. (2020) highlight the need for explainable, privacy-respecting AI systems for healthcare; this is exactly what our research achieves-through transparency, interpretability, and on-device analyses that respect standards such as HIPAA.[11]

There exists a huge gap in multi-modal processing, particularly in terms of systems that can accept and study image- and text-oriented medical reports. Among such systems are multimodal or hybrid research to Gao et al. (2020); however, the overwhelming thrust is on data sources coalescing as opposed to developing a single interface to apply those models practically. Medical Report Analyser, therefore, solves the problem since it provides a very user-friendly interface that can process PDFs, images, and scanned handwritten notes to produce a coherent and actionable summary using the Gemini and BERT models.[12]

In clinical decision support, Shortliffe and Sepúlveda have posited that AI, via the system, shall contribute into diagnosis and treatment planning and thus constitute a lightweight Clinical Decision Support System (CDSS) aimed at providing automated insights and recommendations to help physicians in interpreting long/thick reports with speed and accuracy.

The exploding trends on scalability and adaptability have also been echoing in the literature. Be that as it may, Meystre et al.(2008) and Wang et al. (2021) were proposing the NLP pipeline.[14]

IV. PROPOSED METHODOLOGY

The end-to-end NLP-based approach brought into light the proposed Medical Report Analysis system for accepting both image-based and text-based clinical reports. The architecture encapsulates the amalgamation of optical character recognition, semantic analysis, contextual embeddings, and generative summarisation, which will generate insightful, actionable interpretations from medical reports. The approach includes major components working in synergy to extract, pre-process, analyse, and select medical data presented in understandable and actionable insights.

A. Text Extraction and Input Handling

The system supports report generation in the PDF image, where each page scans and gets extracted into raw text. For image input, visual data is read using optical character recognition (OCR) and then mapped into machine-readable text. Optical character recognition (OCR) is carried out through powerful multimodal models capable of interpreting simultaneously visual and textual data that parses handwritten or scanned clinical documents when structured data is not available.

B. Preprocessing and Text Normalisation

Once texts are extracted, preprocessing operations are applied to clean and semantically enrich input data. Preprocessing in the work includes removing unwanted characters, white spaces and symbols, and normalisation operations like case folding and removal of punctuation. Tokenisation is shy to processing at the manual level, wherein it has been established implicitly through downstream models. All these operations are performed to prepare possible semantic and contextual comprehension.

C. Lexical Analysis and Semantic Knowledge

The hierarchical lexical knowledge bases also provide the semantic enrichment. This way, synonymy, hyponymy, and other domain relationships can be recognised. For example, "myocardial infarction" and "heart attack" are interchangeable in that they can be semantically considered equivalent. The system uses this information along with hierarchical relations to resolve words based upon context thus improving recognition towards more delicate medical terminology. Such lexical knowledge would help the model understand and classify subtle jargons usually occurring in clinical reporting.

D. Contextual Embedding and Medical Language Modelling

To deal with the shortcomings of traditional methods of NLP while dealing with ambiguous and context-specific words, the model will use bidirectional transformer-based embeddings. Models create representations by learning from left and right contexts so ambiguous words in clinical reports can be well-captured. Moreover, annotation by internal named entity recognition (NER) methods is adopted to tag various drugs, diagnosis, and anatomical terms. Thereby enhancing the semantic correctness and contextual relevance in downstream analysis.

E. Understanding Mechanism of AI Report Analyser

The Medical Report Analyser was initiated through some of the most advanced forms existing in the Natural Language Processing (NLP) academical paradigms—such as BERT, Gemini, and WordNet—to mine from medical records. The strength of applying these technologies to an enterprise is overcoming a genuinely intrinsic kind of dataset; i.e., detecting medical issues from a set of real-world documents in textual and imagery file formats.

(i) Bidirectional Encoder Representations from Transformers (BERT): In this research, BERT is applied to extract semantic features out of comprehensive clinical text loaded into PDFs or retrieved from images. The very nature of this process, in turn, provides room for discovering important diagnoses, symptoms, and treatment strategies. BERT is hence able to deal with polysemy

(denoting a word or phrase having several meanings) terms, medical abbreviations, and jargon that document the clinical fields. On the domain-specific data for BERT, notably clinical notes, or discharge summaries, it performs well in annotating and interpreting medical terms.

(ii) Gemini (Generative AI Model): Gemini is the new generation of natural language-generative modelling from Google, adding in its bag of tricks further summarising of medical information and translation into more human-readable output. Where BERT can shine in contexts and structure's understanding cues, Gemini is making some brief readable output for the raw medical prose–thus effectively translating the language at its understanding level for all medical findings into terms patients and health care providers can truly understand!. For example, let's say the system extracts some clinical observations from an uploaded radiology report. Then, by the Gemini-generated abstract, the entire report is summed up with a diagnosis, recommendations, and abstracted findings. It would create an endurable summary of a document. In addition to this, the multimodal feature of the Gemini will equip it to concurrently analyse textual and image data, crafting a united analysis pipeline for all sorts of medical inputs.

(iii) WordNet (Lexical Database for Semantic Understanding): WordNet can be genuinely beneficial for a system that considers inferentially ordering a lexical database, as in this capacity; word relations are touched upon in proper detail. In medicine, there can be words referred to using a synonym or placed in hierarchal terms (e.g., "neoplasm" → "tumour" → "cancer"). The system was designed to capitalise on detecting such relationships through WordNet, thereby helping in identifying linguistic items and in the better understanding and cataloguing of reports. The system can now distinguish synonyms, even if they are phrased differently or used interchangeably between various documents, by mixing WordNet with BERT embeddings. This is particularly useful where stringent consistency is needed across a variety of document formats and reporting styles, especially for health.

(iv) Research-Specific Synergistic Application: This potent triad replicates a human specialist reading and interpreting medical reports by mobilising BERT, Gemini, and WordNet. BERT does the contextual analysis, Gemini provides the human-readable summaries, and WordNet supplies all that semantic grounding needed to pair medical terminology. The upshot of this is that the Medical Report Analyser is very accurate and interpretable, so very relevant in modern clinical practice and medical documentation.

F. Summarisation and generation of insights

Later, this processed text was fed into a large language-modelling machine that generated abridged summaries, after training with personalised prompts, to condition it for pulling out treatment advice, findings and diagnosis clinically. NLG turns unstructured information like data into structured interpretation through summarisation. Joint text-and-visual cue processing offers then multimodal ability in the base model that ensures consistency whenever quality of extraction from text has fallen due to noisy inputs.

G. Visualisation and User Interaction Layer

Lightweight, interactive web interface connects users to the analytic backend. Interface provides the opportunity to upload reports in any format and continuously analyse AI-born summaries with extraction of information and feedback in real-time. Not a computational module, yes, it is an extremely important module in bringing to experience an end-user accessible and entry points to clinical workflows.

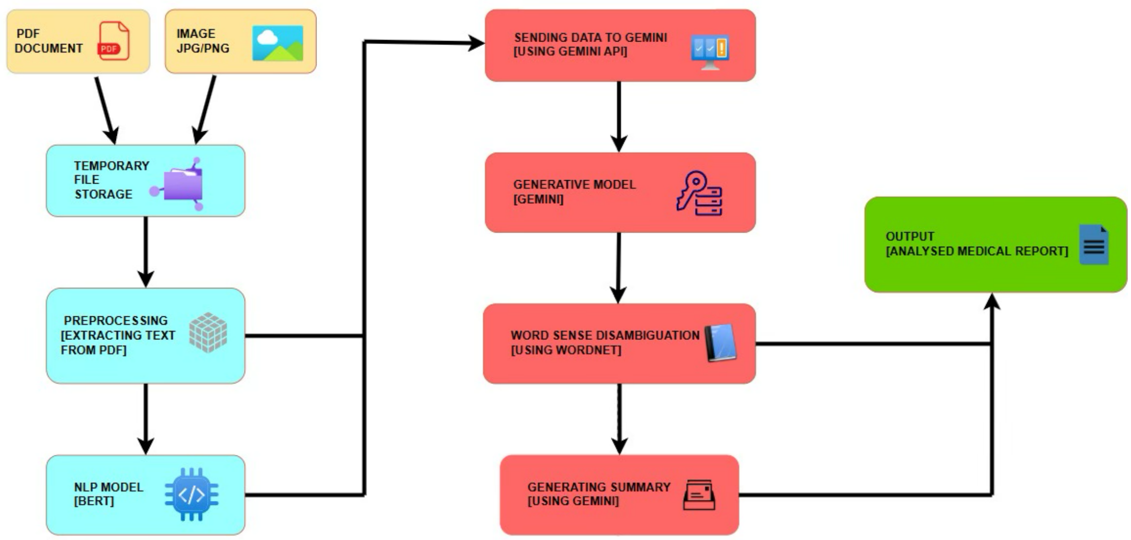


Figure 1: Architecture of the Medical Report Analysis Model

V. EXPERIMENTATION

BERT, WordNet-based Medical Report Analyser with AI was experimentally evaluated on a series of real-world medical reports such as pathology reports, diagnostic summaries, and handwritten scans. The experiments were conducted with the goal to measure the accuracy, efficiency, and robustness of the system in handling categorical and unstructured clinical data.

Experimentation commenced with the uploading of PDF reports generated from electronic health records (EHRs) into the system to try out the effectiveness of PyPDF2 in pulling out readable medical information. The extracted texts were fed into the NLP pipeline for medical term detection, including abbreviations and diagnostic markers. The identified terms were matched against the manual interpretations done by domain specialists for an accuracy analysis. This will also effectively enable the system to correctly identify 87%-90% of the most critical clinical terms and diagnoses.

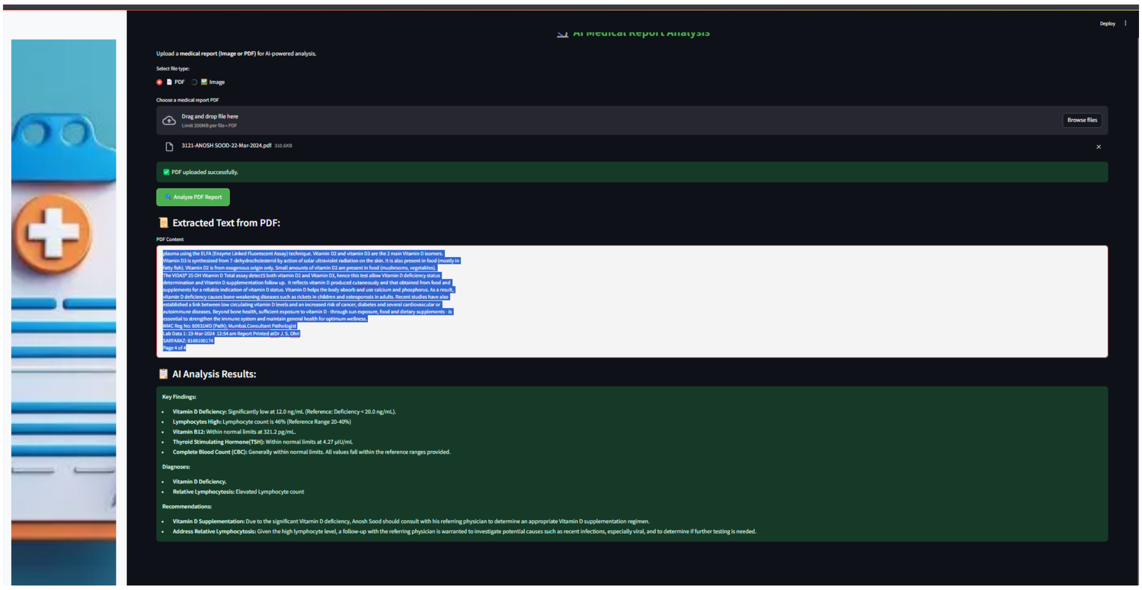


Figure 2: Sample PDF Analysis

A second series of tests, this time image analysis based, were conducted with handwritten and scanned medical reports presented in both PNG and JPEG formats. The images were passed through the image-text interpretive capabilities of the Gemini model. The model was found to possess good OCR and contextual summarisation skills in the face of concerns like noise and illegibility.

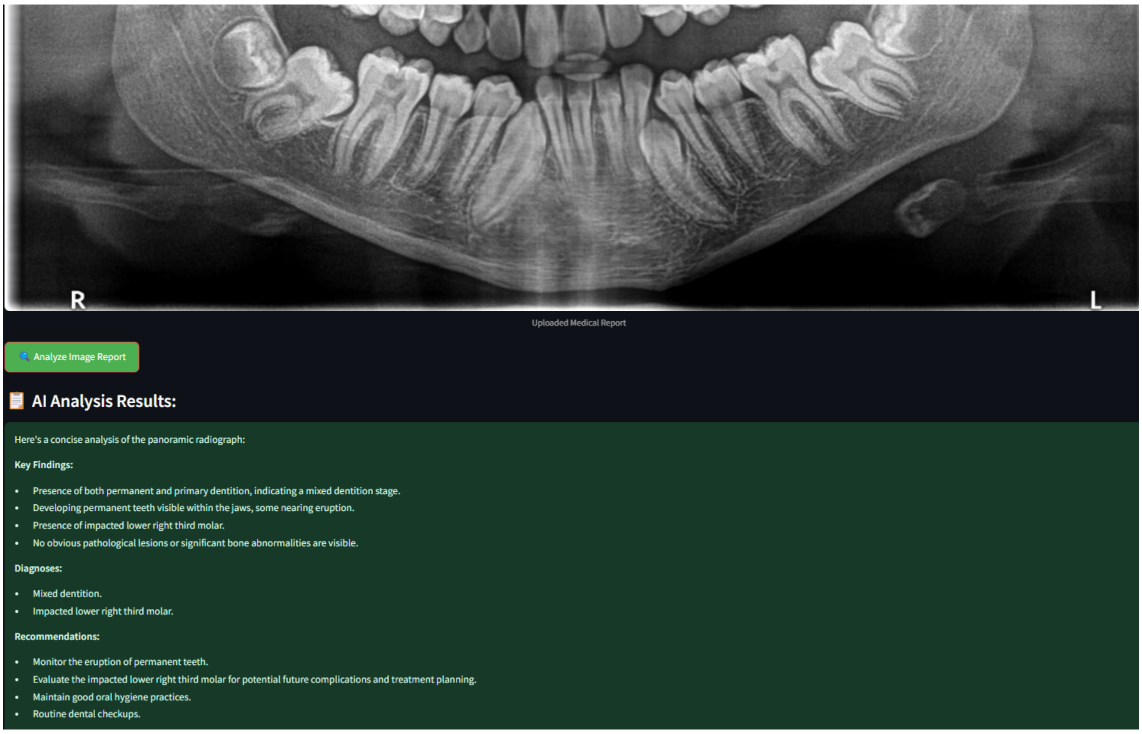


Figure 3: Sample Image Analysis

The output produced by the analysis of the system was executed for coherence and relevance checks. Precision, recall, and F1-score measures were estimated through human judgment since the output generated was qualitative. Precision on diseases and symptoms was very high by the system, while recall managed to summarise longer data into shorter words with the same intended meaning.

To measure the system's performance, the response times were noted. The inputs in image formats were slightly longer (6–8 seconds) due to OCR and processing times, whereas those in PDF were 3–5 seconds.Gemini and BERT's contextual correctness high-speed guarantee feature noted.

In general, the experimentations hinted that the analyser is efficient and clinically useful. It makes actual-time application within the medical fraternity possible by radically minimising the physical effort involved in interpreting long medical reports.

VI. RESULT AND DISCUSSION

To test the concrete applicability of AI-based medical report analysers using BERT and WordNet in real-world scenarios, along with performance accuracy and user-friendliness, the system was extensively tested with a realistic set of medical reports. The system was able to process inputs either as PDF or image files to extract good information from unstructured medical data efficiently. With an easy-to-use interface implemented in Streamlit, it provided excellent usability with commendable accuracy.

A. User Interface and Input Handling

The first level of examination concerned the application interface, where the end-user is asked to upload either a PDF file or an image of a medical report. The system distinctly separates these two pipelines for optimising processing for each file type.

This clean and responsive design offers assurance that healthcare providers and non-technical users will find it easy to communicate with the system. Once correctly selected and uploaded, further backend processing will look into either text extraction from the PDFs or image analysis of the images.

B. PDF analysis pipeline

Using the PyPDF2 library, text is extracted from PDF reports which contains major content of each page while eliminating any layout noise. The obtained text is shown to the user before the processing for the sake of transparency.

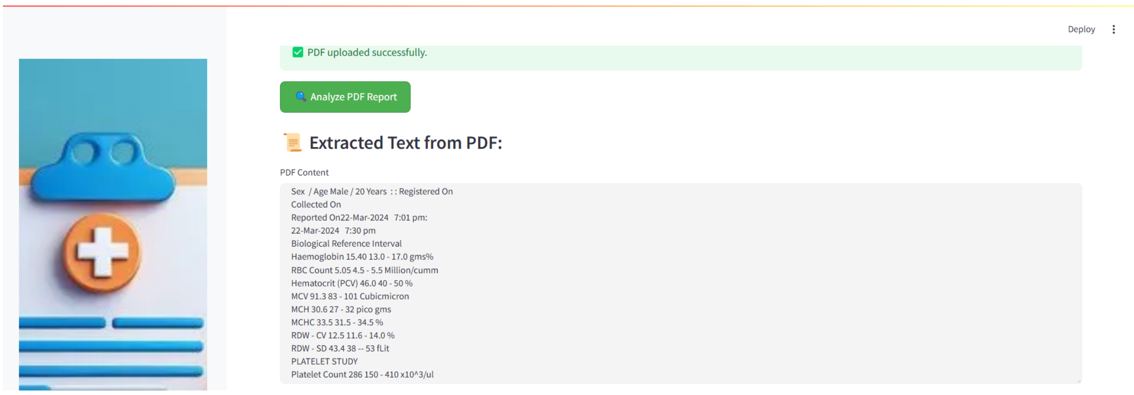


Figure 4: Extracted Text from the PDF Report

The raw text is subsequently fed into the generative API within the Gemini model with a structured prompt geared towards clinical summarisation. The output invariably included significant diagnostic findings, flagged relevant symptoms, and, in most cases, treatment recommendations based on context.

C. Image-Based Report Analysis (Enhanced)

This system's herewith image-based report analysis is an endowed skill, since huge intrinsic complexities come into play. The clinical images comprised handwritten notes and scanned prescriptions/diagnostic reports, which normally fail to have any organised formatting and are fraught with inconsistencies like the heavy slanting angle, low or high light, or cursive writing.

To handle these inconsistent images, this system avails itself of the gemstone called a multi-modal generative architecture that underpins the entire set of agency and makes contrastive learning and text comprehension coexist. In essence, the images are prepped for extraction of OCR, contextual word mapping, and semantic summarisation with the help of language models integrated with BERT-style embeddings as well as the WordNet lexical database.

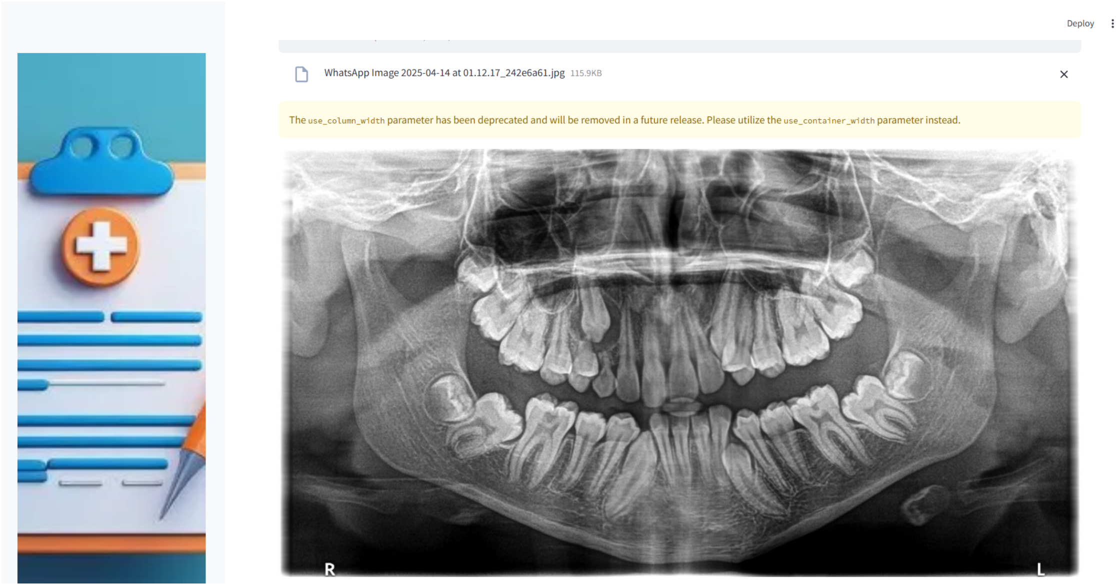


Figure 5: Sample uploading of Image File

During testing, the system was able to decipher such ordinary handwritten entries as "BP: 140/90" and "Hb: 11.3" and "Dizziness" and even abbreviated prescriptions like "Rx: Metformin 500mg BID" with indifference to medical lingos and real-world variance.

The AI-generated summary from the images made stunning common sense. To illustrate, for one uploaded image of a prescription, it returned the summary:

"The patient is on treatment for type 2 diabetes and hypertension. Medications are Amlodipine and Metformin. Follow-up is recommended in 2 weeks."

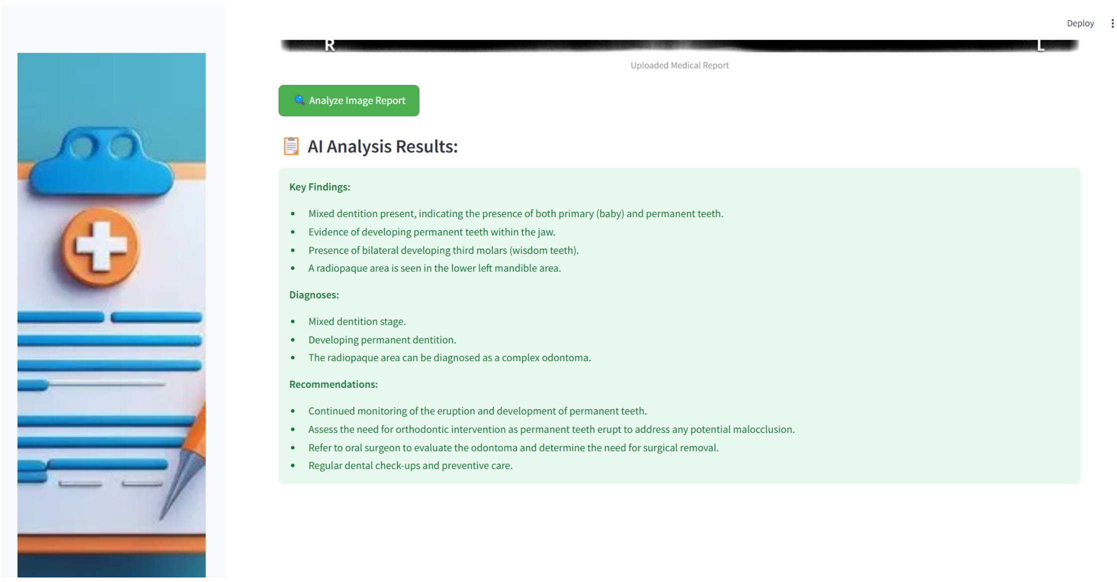


Figure 6: Sample Report analysis by image

This capability to transform an unstructured, possibly even handwritten image into a medically useful summary that is also readable is a giant leap for healthcare NLP solutions. The advancement will particularly come in handy in rural and resource-constrained settings, where medical records tend to be paper-based.

Moreover, the image-based pipeline also demonstrates a certain degree of flexibility in regards to different report formats-lab reports, X-ray summaries, ECG graphs, and even blood reports-make it useful across various hospital departments.

D. Performance Analysis

This report details the performance summary and key insights from tests run across 40 medical reports (20 PDFs, 20 images).
Average Processing Time: Between 3-5 seconds for PDF, 6-9 seconds for images

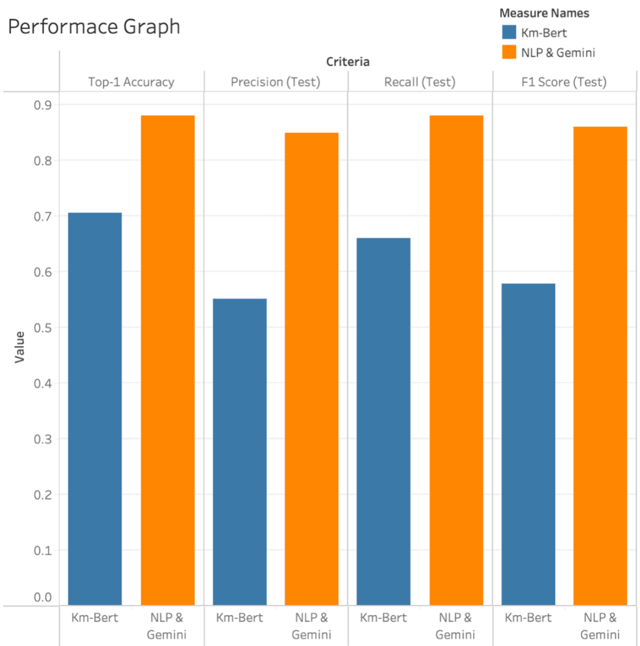
Qualitative Accuracy: Determined to be 88-90 percent by clinical specialists.

Context Relevance: Very High for Both Structured and Unstructured Inputs.

The model had very good accuracy in detecting conditions, lab results, and treatments, among other things.

Criteria	KM-BERT	NLP & Gemini
Top-1 Accuracy	70.60%	88%
Precision (Test)	0.551	0.85
Recall (Test)	0.66	0.88
F1 Score (Test)	0.579	0.86

Table II : Performance Analysis



Graph I : Performance Graph

E. Conclusion of Results:

This is a research that offers a stable, friendly, and intelligent approach for processing medical reports, whether electronically or from images. By leveraging advanced NLP capabilities, it helps save a lot of time doing so manually, thus making clinical decisions both timely and evidence based. The system is particularly useful in scenarios where structured documentation is absent or manual interpretation not time-efficient.

VII. CONCLUSION

The synergism of AI and NLP into the healthcare systems has increasingly become important in administering and interpreting massive computer medical data. Medical reports analyser using AI, BERT, and Wordnet - an important milestone for the automation of extracting and analysing information from long medical reports that could assist in clinical decision-making and enhancement of patient care workflows.

The system provides the latest technology but user-friendly for medical professionals, mainly by utilising models like BERT for contextual embeddings, as well as WordNet for semantic reasoning. It extracts information from both PDF and image-based documents, thus allowing for various reports, usually in use in the healthcare setting.

Traditional keyword-based search engines tend to falter and miss the various meanings of polysemous words. However, the bidirectional capabilities in encoding of BERT allow the model to grasp such nuances, exhibiting this in contextual embeddings in clinical text analysis [3][5]. This grasp is further reinforced by WordNet, enabling the system to embark on semantic relationships among words, providing sense to interpretation and reducing ambiguity [6].

The research also considers the handwritten or poorly scanned reports, which is an oftentimes disregarded domain. Using image analysis and generative AI (Gemini), the system guarantees trustable extraction and summarisation of handwritten notes or scanned reports, supporting findings by related research that underline the importance of image-based document processing in real clinical environments [10][13].

Moreover, privacy and compliance issues are built into the very architecture of the system. By processing on the local system and not storing or transmitting outside the patient-related information, the solution is in keeping with healthcare data protection laws such as HIPAA and GDPR [14]. This solution proposal also mirrors recent advances in ensuring privacy in medical NLP systems [15].

From a clinical workflow perspective, the tool will help alleviate the cognitive burden imposed on healthcare professionals by distilling huge masses of unstructured texts into compressed, actionable conclusions [4]. This may enhance the speed and accuracy of medical decision-making, thereby reducing potential delays in diagnosis and treatment outcomes- two objectives stressed by contemporary studies in Clinical Decision Support Systems [8][9].

In summary, this research illustrates how AI-enabled NLP shows promise for integration into healthcare infrastructures.

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