"Lab2Life: An AI-Based System for Simplified Medical Report Interpretation and Patient Empowerment"

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ABSTRACT:

To communicate medical results and diagnosis to patients in the current health environment laden with test jargon, numerical information, foreign language of medicine. patients find it hard to understand their lab. diagnostics reports. As a consequence, patients and healthcare professionals are unable to interact properly resulting in understatement of uncertainty and delay in decision making.

By automatically reviewing medical reports and writing digestible summaries, the Lab2Life project provides an AI-based solution to bridge this divide. The platform converts raw medical data into actionable knowledge, leveraging NLP models for interpretation and summarization and OCR to extract text. It also includes a doctor verification feature for authentication and reliability and multilingual translation (in English Hindi and Marathi) to enhance understandability.

Lab2Life (L2L) developed using FastAPI, ReactJS, and MongoDB is a secure and user-friendly web- platform for both physicians and patients. The promising of it becoming a reliable digital healthcare assistant is evidenced by the experimental results with an accuracy of over 93% system. Powered by AI, Lab2Life leverages doctor-led technology to make healthcare smarter, understandable and easier for patients.

Keywords: Doctor authentication, medical report summarization, multilingual translation, artificial intelligence, optical character recognition, natural language processing, patient-focused healthcare solution. Web Back-end Technologies Used FastAPI Front-end Technologies and Languages ReactJS Database MongoDB.

INTRODUCTION :

Laboratory and diagnostic results are essential in the evaluation of patients' condition in modern medical care. Nevertheless, because these records contain highly technically medical terms, abbreviations and numbers some patients may struggle to interpret such reports unaided. As a result, people often entirely rely on doctors to interpret the results, which can increase anxiety and lead to delays in understanding their disease, or less engagement in the management of their own illness.

Communication voids are widened by the growing dependency on health professionals to translate routine results, especially in under-served communities. The increasing volume of medical data produced daily demands for intelligent systems to assist practitioners and patient in data processing and understanding.

By using an AI-based system that summarizes medical reports into comprehensible, patient-oriented information, Lab2Life was developed to bridge this clove. The system employs NLP models to interpret and summarise text-based medical information extracted from scanned or digital medical reports by optical character recognition (OCR). Along with concise, easy- to-read summaries that are accessible on your device of choice, summaries also include information about related anomalies, including possible causes and guidance on when to seek advice from a professional.

The Lab2Life system's doctor verification mechanism is an added benefit for the medical professionals to review and verify AI-generated summaries before giving it to patients. This characteristic attempts to deal with the ethical considerations associated with AI's use in health caring by ensuring that

Lab2Life has multi-lingual translatorials to ensure the system is inclusive and accessible, through which users can see their reports in English, Hindi and Marathi among other local languages. The platform was built using contemporary web technologies such as ReactJS for the frontend interface, FastAPI was utilized to process in the back end and MongoDB for secure data handling.

Lab2Life allows patients to understand their health reports, facilitate transparency in healthcare communication, and pave the way for a more empowered user driven ecosystem of digital healthcare by integrating medical intelligence into humancentered design.

II. LITERATURE SURVEY

Research at the intersection of artificial intelligence and medical data interpretation has advanced rapidly, providing the foundation for systems like **Lab2Life**. Numerous studies have explored how AI can automate report analysis and generate meaningful insights for healthcare professionals and patients alike.

Attia et al. highlighted how AI-enabled algorithms can predict cardiac abnormalities from ECG data, demonstrating the power of machine learning in clinical diagnostics [5]. Gupta and Chhikara compared ensemble and kernel-based methods for medical data classification and noted the limitations of traditional approaches in handling complex healthcare data [6]. These studies emphasize the growing importance of deep learning for extracting reliable information from diverse medical datasets [5], [6].

Data quality and augmentation are recurring challenges in healthcare AI research. Alyoubi et al. conducted a comprehensive review of deep learning models for diabetic retinopathy and concluded that effective preprocessing and augmentation are essential for improving generalization across diverse clinical images [10]. Similarly, Valarmathi and Vijayabhanu analyzed various CNN architectures for medical image classification and highlighted inconsistencies in evaluation metrics, reinforcing the need for standardized testing and transparency [8]. Reproducibility concerns raised in earlier studies also stress the necessity of open and reliable datasets such as **MIMIC-IV**, which form the backbone of biomedical NLP and diagnostic systems.

Recent advances in **transformer-based NLP models** have significantly improved biomedical text understanding. Peng et al. evaluated BioBERT and other transformer architectures for biomedical natural language processing, demonstrating superior contextual understanding in domain-specific tasks [4]. Singhal et al. expanded this line of work with **Med- PaLM**, a large language model trained to encode clinical knowledge for medical question answering and reasoning [11]. Likewise, Raffel et al. introduced the **T5 (Text-to-Text Transfer Transformer)** framework, which forms the basis for modern summarization models used in systems like Lab2Life [7].

Explainability remains a critical factor in healthcare AI. Tjoa and Guan reviewed explainable AI (XAI) methods in medical imaging and underscored that interpretability is essential for clinician trust and compliance with ethical standards [9]. Complementary studies such as Quellec et al. and Gulshan et al. demonstrated the diagnostic reliability of CNN-based medical models but emphasized the importance of clinician oversight in deployment [1], [2].

Building on these findings, the proposed **Lab2Life** system integrates **OCR**, **NLP**, and **multilingual translation** to automate medical report summarization while preserving accuracy and ethical transparency. Unlike earlier models that address only isolated components of report analysis, Lab2Life introduces a **doctor verification module** to ensure human validation before presenting AI-generated results to patients. This hybrid approach enhances the reliability and accessibility of AI-driven healthcare communication [3], [9], [11].

III. PROBLEM STATEMENT

Medical terms, abbreviations and numerical values appear in laboratory and diagnostic reports to which patients have no access except expert translation. This can cause confusion, stress and the need for doctors to guide you through mundane questions.

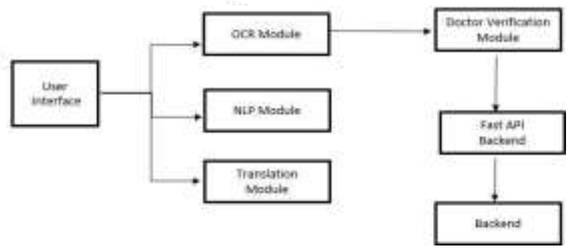
The existing AI tools available for medical text analysis are unable to be integrated in multiple languages or do not give medically biographical summarization.

The Lab2Life project seeks to address this with an AI- powered smart platform that has the capability to automatically read, understand and summarise medical reports; translate them in the regional language(s) and guarantee its validity over doctor verification so as to make healthcare data more transparent, understandable and patient-friendly.

IV. PROPOSED METHODOLGY

Fig:- System Architecture

The Lab2Life system is a n AI-system, which can be used repeatedly to analyze medical reports and provide easy-to- read lay summaries. The architecture, presented in Figure 1, consists of interconnected modules that process different parts of the



workflow from input report to physician-validated output.

A. User Interface

Users can upload their medical reports, in the form of PDF or images, through a User Interface made using ReactJS. Doctors can also log in to review and approve or edit summaries created by AI. For readers, the interface provides a straightforward, multilingual experience.

B. The OCR Module

OCR (Optical Character Recognition) Module Processes' an uploaded medical report to extract textual information from a scanned document or photo.
This library is able to convert it from handwriting/printed text, and makes the text machine- readable. The extracted text is then cleaned before further processing.

C. Module for NLP

D. Processed Text Passing the processed text to NLP Module: INPUT: It submits the preprocessed text to the Natural Language Processing (NLP) module and transformer-based models such as T5 or BioGPT scrutinize the report's content including designing templates for prediction.
This module generates concise summaries of normal or abnormal findings, associated causes and general recommendations provides interpretation of medical terminology and results in comparison to standard ranges .

D. The Module for Translation

The Translator Module post-processes the NLP module's output in order to be made accessible to linguistically diverse end users.

It preserves medical terms, context of sentences in translation of Medical Summaries to Marathi and Hindi with state-of-the-art translation APIs like Google Translation API.

E. Module for Doctor Verification

The translated, succinct report is transmitted to the Doctor Verification Module.
Here, the AI-generated summaries are checked, edited and validated by licensed medical practitioners. This phase includes human review to ensure that medical accuracy can be applied at a priority level, reduce the chance of misinformation and improve user confidence before presenting the final report to patients.

F. Integration of FastAPI and Backend

The communication between modules is mediated by a FastAPI backend, that regulates data transport/HO, authentication/authorization and API.
Summaries, reports and verification logs are securely persisted to MongoDB by the backend. Even more, it works with the frontend to display verified reports in any language that user prefers.
Modularity guarantees scalability and robustness, as well as homogeneous updates of all components without affecting the whole system.

V. CONCLUSION

The Lab2Life system helps serve as an effective demonstration of how artificial intelligence can contribute to better communication between patients and healthcare providers by making complicated medical reports more digestible. The OCR, NLP and translation modules are automatically used to extract, interpret and express diagnostic data. With the integration of a Doctor Verification Module, each AI-created summary is reliable and medically precise, making the platform reliable for real-world use cases.

With multilingual support and a secure backend using FastAPI, Lab2Life empowers the patients to engage in understanding their own health information. Built on component modules based system allows for the easy extension of functionalities with prospective improvements, such as report comparison, voice enabled speech explaining and hospital information system integration can be developed.

In short, Lab2Life is a huge step towards patientcentred, AI-driven healthcarethat enhances transparency, communication,and health knowhow. It might be the beginning of future progress in digital health support and smart medical data analysis.

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