Medisense Ai Using Large Language Models for Multi-Disease Prediction

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Abstract—**Artificial intelligence is becoming an increasingly popular tool in healthcare organizations to help expedite and enhance the quality of clinical decisions. Most of the currently existing prediction tools are disease-specific and rely almost entirely on structured inputs like glucose level, blood pressure, cholesterol or body mass index. In this work, I will introduce a multi-disease prediction platform, MediSense AI, that incorporates both traditional machine learning models and Large Language Models to enhance clinical outcomes and user experience. The proposed system predicts the risk of Diabetes, Heart Disease, Liver Disease, and Parkinson's Disease by accepting both medical parameters, and symptom descriptions that are written in natural language. K-Nearest Neighbors, Random Forest, XGBoost, Naive Bayes, and Support Vector Machine are algorithms used depending on the disease and data required. The LLM aspect aids in the interpretation of symptoms, the explanation of results in a simple language, and the Humanization of the application itself. The platform is developed as a web app in Python, Streamlit, and Django. The study suggests that a hybrid solution can enhance accessibility, response time and usability during preliminary health-risk assessment.**

Index Terms—**Multi-disease prediction, Large Language Models, healthcare AI, machine learning, Streamlit, Django, KNN, Random Forest, XGBoost, disease detection, medical chatbot, predictive analytics.**

I. INTRODUCTION

Healthcare Artificial intelligence is transforming how healthcare systems can detect risk, process patient data and aid in early diagnosis. Early identification of chronic diseases can be used to decrease complications, reduce the cost of treatment and improve patient outcomes. Majority of the existing prediction systems are developed in relation to a single disease and require the user to key in fixed numerical values like glucose level, blood pressure, cholesterol and BMI. However, in real life scenarios, multiple users report of their discomfort using ordinary language, such as, noting that they experience chest pain, dizziness, fatigue, or tremors. The unstructured description of this type cannot be directly interpreted by the traditional machine learning models. MediSense AI fills this gap by launching disease-specific machine learning models together with Large Language Models on a single interactive platform. The system receives structured medical values and natural language symptoms, processes the information and directs the information to the applicable prediction model and then displays the probable health risk to the user. The platform supports Diabetes, Heart Disease, Liver Disease, and Parkinson's Disease in a single application, thus reducing the need for individual tools and enhancing patient and healthcare provider accessibility. Large Language Models enhance the experience by comprehending statements about symptoms, requesting more precise information when necessary, and explaining the results in non-technical language. The app is coded in Python-based technologies, and it uses Streamlit to provide a user-friendly interface and Django to process the requests. Prediction is performed in real-time on trained models to supply the system with quick preliminary advice to users with little technical expertise.

II. LITERATURE REVIEW

Table 1 summarizes important studies related to machine learning, deep learning, language models, and healthcare prediction.

Author(s)	Year	Research Focus / Title	Methodology	Major Contribution	Limitations / Gaps	Outcome
Choi et al.	2016	Doctor AI: Predicting Clinical Events	Recurrent neural networks applied to sequential electronic health records	Modeled patient history as a time sequence for future clinical-event prediction	Depends on large longitudinal datasets and offers limited interpretability	Improved prediction of future diagnoses and medication needs
Miotto et al.	2016	Deep Patient System	Unsupervised deep learning on electronic health records	Learned hidden patient representations from high-dimensional health data	The model behaves as a black box and is difficult to explain clinically	Showed stronger disease prediction than several traditional approaches
Esteva et al.	2017	Skin Cancer Classification	Convolutional neural network for image-based diagnosis	Demonstrated dermatologist-level performance on skin lesion images	Requires large labeled image datasets and substantial computing resources	Established the value of deep learning in medical image analysis
Chawla et al.	2002	SMOTE Technique	Synthetic oversampling for imbalanced classification datasets	Reduced bias toward the majority class in medical prediction tasks	Can add noisy synthetic samples if applied without validation	Improved classifier behavior on imbalanced healthcare data
Singhal et al.	2023	Large Language Models in Healthcare (Med-PaLM)	Medical question answering with large language models	Showed that LLMs can represent and explain clinical knowledge	Requires careful validation because generated responses may be incorrect	Supported the use of LLMs for medical-language understanding
Rajkomar et al.	2018	Scalable Deep Learning with EHR	Deep neural networks trained on large electronic health records	Handled diverse healthcare data at scale for multiple prediction tasks	Training and deployment require significant computational infrastructure	Produced strong predictive performance on real clinical datasets
Huang et al.	2017	DenseNet Architecture	Densely connected convolutional neural network	Improved feature reuse by connecting layers more directly	Designed mainly for image data rather than tabular medical records	Increased efficiency and accuracy in image-recognition tasks
Chen and Guestrin	2016	XGBoost Algorithm	Gradient-boosted decision trees	Provided a scalable and accurate method for structured-data prediction	Needs careful hyperparameter tuning to avoid overfitting	Became a strong choice for tabular healthcare classification
Vaswani et al.	2017	Transformer Model	Self-attention mechanism for sequence modeling	Captured contextual relationships without recurrent processing	Requires large datasets and high training cost for best performance	Transformed modern natural language processing systems
Devlin et al.	2019	BERT Model	Pre-trained bidirectional transformer language model	Improved contextual understanding of words and sentences	Computationally demanding during training and fine-tuning	Raised performance across many language understanding tasks
Lee et al.	2020	BioBERT	Biomedical adaptation of BERT	Improved language processing for biomedical	Requires domain-specific corpora and task-level tuning	Enhanced performance on

				documents and terms		biomedical text-mining tasks
Johnson et al.	2016	MIMIC-III Dataset	Public critical-care database for healthcare research	Provided a large benchmark dataset for clinical machine learning	Requires careful preprocessing, privacy awareness, and clinical interpretation	Widely adopted for evaluating healthcare prediction models
He et al.	2016	ResNet Architecture	Deep residual learning for image recognition	Used skip connections to address the vanishing-gradient problem	The architecture is complex and mainly suited to image-based tasks	Improved the depth and accuracy of deep neural networks

Table 2: Study-wise evaluation of healthcare prediction approaches

Ref. No.	Author(s) and Year	Study Focus	Key Finding	Relevance to MediSense AI
[1]	Choi et al., 2016	Doctor AI for clinical-event prediction using RNNs	Sequential patient histories can improve future risk prediction	Supports the need to consider patient context when predicting disease risk
[2]	Miotto et al., 2016	Deep Patient using unsupervised learning on EHR data	Hidden patterns in patient records can improve disease prediction	Shows the value of learned health-data representations
[3]	Esteva et al., 2017	Deep learning for skin cancer classification	Image-based neural models can reach specialist-level performance	Highlights the potential of AI-assisted diagnosis beyond tabular data
[4]	Chawla et al., 2002	SMOTE for imbalanced datasets	Synthetic sampling can improve minority-class detection	Useful for medical datasets where positive disease cases are limited
[5]	Singhal et al., 2023	Med-PaLM and clinical language understanding	LLMs can respond to medical queries with contextual explanations	Motivates the symptom-understanding and explanation layer in MediSense AI
[6]	Rajkomar et al., 2018	Deep learning on large-scale EHR data	Large clinical datasets can improve predictive accuracy	Shows the importance of scalable pipelines for healthcare prediction
[7]	Huang et al., 2017	DenseNet for deep visual feature learning	Dense connections improve feature reuse in deep networks	Relevant for future expansion into medical-image analysis
[8]	Chen and Guestrin, 2016	XGBoost for structured-data classification	Boosted trees provide strong accuracy and scalability	Supports the use of XGBoost for heart-disease prediction
[9]	Vaswani et al., 2017	Transformer architecture	Attention helps models understand long-range language relationships	Forms the foundation for the LLM component of the system
[10]	Devlin et al., 2019	BERT language model	Pre-training improves language understanding across tasks	Shows how contextual models can process symptom descriptions
[11]	Lee et al., 2020	BioBERT for biomedical natural language processing	Domain-specific language models improve medical text analysis	Supports future use of healthcare-specialized LLMs
[12]	Johnson et al., 2016	MIMIC-III healthcare dataset	Open clinical datasets enable reproducible healthcare AI research	Provides a reference point for dataset design and benchmarking
[13]	He et al., 2016	ResNet for image recognition	Residual connections make very deep models trainable	Relevant to later image-based disease-detection modules

III. METHODOLOGY

MediSense AI methodology consists of a series of steps or a pipeline that ensures that effective and useful multi-disease prediction is indeed supported.

Dataset Selection: Healthcare datasets are taken on good public sources, including:

- UCI Heart Disease Dataset
- PIMA Diabetes Dataset
- Indian Liver Patient Dataset

Such datasets include clinically significant variables like age, glucose level, blood pressure, cholesterol, BMI among other disease specific variables.

Data Preprocessing: The crude datasets are pre-prepared and then trained using the following steps:

- Missing-value data, with appropriate imputation tools.
- Detection and treatment of outliers.
- Normalization or standardization to scale features.
- Segmentation of data into training data and testing data.

This step enhances the quality of data and enables the models to acquire smoother patterns.

Model Training: Training various machine learning algorithms is done based on the properties of each disease dataset:

- KNN to predict Diabetes.
- Prediction of Liver Disease using random Forest.
- XGBoost Heart Disease prediction.

Both models use the training data to obtain a relationship between the health parameters and the disease outcomes.

Model Evaluation and selection: The trained models are compared against standard classification measures:

- Accuracy
- Precision
- Recall
- F1-score

Each of the disease categories will be concerned with the model with the most balanced performance.

Model Persistence: The chosen models are passed to Python Pickle to be reused stepwise when predicting without retraining the models again.

Web Integration: The application is deployed with the help of:

- Streamlit due to the user interface.
- Django to do backend processing.

The design facilitates real-time communication and takes out the prediction logic and the presentation layer.

Prediction Phase: The user is required to key-in health parameters or symptoms information.

- Application already processes the input and conveys it to the necessary model.
- The model chosen approximates the disease-risk type.
- The answer and reason are shown to the user instantly.

IV. COMPARATIVE STUDY WITH EXISTING RESULTS

Model	Accuracy	Speed	Interpretability	Best Use	Model Type
KNN	High	Medium	High	Diabetes prediction	Instance-based classifier
Random Forest	Very High	Medium	Medium	Liver disease prediction	Ensemble tree classifier
XGBoost	Very High	High	Medium	Heart disease prediction	Gradient-boosting classifier
SVM	High	Medium	Medium	Binary disease classification	Margin-based classifier
Logistic Regression	Medium	High	High	Baseline medical-risk model	Linear probabilistic classifier

V. CONCLUSION

MediSense AI illustrates how machine learning with Large Language Models can be applied to develop an accessible multi-disease prediction platform. As opposed to traditional tools that would be focused on one disease at a time, the proposed system would offer a single interface that would be Diabetes, Heart Disease, Liver Disease, and Parkinson's Disease prediction tool. The KNN, Random Forest, XGBoost and similar classifiers support the high accuracy analysis of structured medical data, whereas the LLM layer allows the analyzer to work with more complex (symptom descriptions) and less interpretable (result) forms of output. The online resource allows a very quick and convenient method of conducting pre-medical examination with the help of preliminary health-risk assessment before medical consultation. Integrating parametric information with unparametric symptom entry enhances usability and eliminates the need to access several diagnostic software packages. Its conversational design is also more engaging to the user since the system is able to explain results and request other information as well as pointing users to appropriate next steps. The project presents the increasing significance of AI-based medical technologies in clinics, hospitals, which telemedicine provide, and remote communities where IM health advice might not be as timely as needed. As datasets grow, validation improves, and application to additional diseases, MediSense AI can be expanded to become a more comprehensive digital health assistant to support early detection, proactive treatment, and enhanced patient decision-making.

VI. FUTURE SCOPE

The improvements to the system in the future could consist of the following:

- Extension to other diseases like cancer, kidney disease, malaria etc.
- Interaction by voice ability to obtain medical assistance without hands.
- Multi-language/ wider regional/accessibility.
- Connections with wearable devices to monitor the health 24/7.
- Deep learning-based modules of image-based diagnosis.
- Accessible patient fragment management and patient access.
- Cloud solutions installed on a hospital, clinic, or healthcare network.
- Customized health advice based on generative AI, which has been clinically tested.

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