DeepMed: AI-Powered Drug Recommendation System

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Abstract. Developments in the implementation of artificial intelligence in medicine have changed the way that clinical decision-making is conducted. DeepMed is an AI-based prescription recommendation network, which aims to generate effective,susceptible and personalized medicine recommendations using patient-specific features. It accepts ages, gender, and diagnoses as inputs and suggests critical pieces of information like "drug name," "dosage" (in what units), "duration," "frequency" (how often a day), "route," and "indication". DeepMed employs method from state-of-art machine learning model, especially ClinicalBERT, a pre-trained deep learning transformer model on electronic health records (EHRs) and clinical data. This allows the system to grasp complicated medical situations, extract patient details quite right and provide accurate drug advice. DeepMed also improves the prediction performance and reduces human errors in drug treatment compared to the large-scale data analysis. Furthermore, the system includes a real- time data processing function for the provision of the latest recommendations in accordance to up-to-date Medical guidelines. This AI-powered Clinical Decision Support System (CDSS) provides data-analytics driven input tohahealthcare agent to be safer with the patient and to make optimized decision for the treatment. DeepMed is conceived to help doctors in well-informed recommendation decisions thereby minimizing the chance of Adverse Drug Reactions (ADRs) and leads to better overall patient outcomes. Large scale testing and validation is used to conclude that this model is able to target the problem of drug errors, and on the same time, it operates quickly and provides drug prescriptions easily and efficiently out of hospital. In this paper, we examine the transformative impact of AI based prescription systems on contemporary health care, and elaborate on their relevance in enhancing patient path and optimizing medical procedures.

Keywords: ClinicalBERT, Drug Recommender System, Clinical Decision Support System, Electronic Health Records, AI in Health Care.

1 Introduction

Medical systems experience many difficulties while recommending appropriate medication since the whole process needs serious consideration of various factors such as patient history, current health problems, drug interaction, and accurate dosages. Human mistakes, like misunderstanding the clinical records, wrong calculation of dosages, and lack of consideration of potential drug interaction, can result in ADRs. These ADRs may vary from mild side effects to life-threatening conditions, finally affecting patient safety and healthcare

ICITSM-Part I 2025, April 28-29, Tiruchengode, India

DOI 10.4108/eai.28-4-2025.2357802

outcomes. Moreover, patient variability variations in age, genetic predispositions, metabolism, and pre-existing health conditions makes it challenging to use a one-size- fits-all strategy in drug recommendations. Numerous studies have delved into public perceptions and attitudes toward online health resources. A recent cross-sectional study in Saudi Arabia, for instance, surveyed 1363 participants, revealing a slight female majority (56.2%) and a mean age of 30.73 $\pm$12.3 [2].

The healthcare system is pressured to provide treatment recommendations that address patients' specific needs. These problems are reflected in the forms of misdiagnosis, late treatment plan, drugs conflict, inaccuracy of the dosage and so on, with badly effected to the patient health and increased medical costs [3]. This strategy is intended to reduce toxicities and to tailor treatment recommendations, leading to improved patient care in general [6]. In traditional clinical settings, clinicians leverage knowledge, guidelines and historical data to prescribe drugs. Conventional methods for disease prediction depend up on the knowledge of clinician and also the results of specialized test which is time consuming, expensive and constrained by the accessibility of the expert doctors [5].

Yet, research shows that drug errors account for a high proportion of hospital re-admissions and adverse drug reactions (ADRs), resulting in high healthcare expenditure and compromised patient safety. The requirement for a more accu- rate, data-driven, and automated method of recommendation decision-making has fueled the use of artificial intelligence (AI)-based systems in healthcare. Early and accurate disease prediction can benefit people and save lots of time [1]. Health- care systems are increasingly recognizing the transformative potential of ML in handling vast datasets and deriving meaningful insights. The project's primary focus is on developing a comprehensive solution that combines predictive modeling for disease identification with an intelligent recommendation system for connecting patients with specialized healthcare providers [9]. No Medicine recommendation available to cure our illness. To promote professional and personalized healthcare, we pro- pose an innovative framework, Heath-LLM, which combines large-scale feature extraction and medical knowledge trade- off scoring [10]. By developing a Health Advisor system using machine learning, we can revolutionize the way to diagnose the diseases, leading to significant improvements in one's own health [4]. AI, and more specifically deep learning and natural language processing (NLP), has demonstrated huge potential in revolutionizing medical decision-making. Of all these developments, ClinicalBERT, a task-specific transformer model, has also proved to be a forceful instrument for interpreting medical texts of complexity.

2 Literature Survey

Prajapat et al.[1] (2024) developed a hybrid system incorporating various classifiers such as Support Vector Machines, Random Forest, Gradient Boosting, and K-Nearest Neighbors. Their approach utilized a dataset containing 132 symptoms across thousands of records to predict multiple diseases and recommend appropriate medication. The system showed very good precision, recall, and accuracy, supporting the benefit of integrating models to enhance healthcare decisions.

Garapati et al. [2] have suggested using a dual system of data mining and NLP in making healthcare decisions. The system employs sentiment analysis and classification technique to provide personalized drug recommendations by analyzing the hospital records and patients comments. The potential power of this approach when combining text mining and machine learning algorithms for better treatment efficacy is highlighted in the current report.

Alsubhi et al. [3] (2025) suggested the use of Bayesian Networks to explain associations of diseases and drugs and the associated side effects. They realized a system that incorporated high predictive accuracy and strong interpretability, a critical prerequisite for clinical application. This approach helps close the gap between (otherwise uninterpretable) black-box models and interpretable decision making in healthcare.

Maithili et al. [4] (2024) proposed a web health advisory system based on content based filtering and machine learning for recommending medicine and health measures. By allowing users to add their symptoms and medical history to the post, the system also aims to provide greater accessibility to accurate medical content, and help in preventing self-diagnoses.

Mahata et al. [5] (2023) where K-NN is used for disease prediction. Their model used symptoms for fast and interpretable predictions, and we also consider it simple and applicable to real-world healthcare settings.

Patil et al. [6] developed the combination of machine learning and sentiment analysis. They utilized the VADER tool and their model to generate recommendations of drugs based on the user reviews and to estimate diseases through classifiers such as Naive Bayes and Logistic Regression. We used a weighted ensemble approach to reinforce recommendation accuracy from symptom-based and patient experience-based data.

Tomar et al. [7] (2024) proposed a hybrid model whose; method integrates CNNs with SVMs. This method was intended to analyze medical imaging data as CT and MRI scans, in combination with the textual input. It was known for its high performance in disease diagnosis such as Parkinson’s, diabetes, and brain tumor and hosted web-interface, for user convenience.

Bharath et al. [8] (2024) concentrated on multi-disease prediction by employing methods such as Random Forest, SVM, and Decision Trees. They wanted to focus on early detection of well-known diseases, including heart disease, liver problems and cancer, and the results were very accurate. The study emphasises the value of achieving a balancing point between algorithmic efficiency and general disease coverage.

Raghunad Reddy et al. [9] (2024) proposed a Naive Bayes-based disease prediction framework that features a recommendation system for linking referrers with suitable experts. They have taken factors such as doctor experience, review, consultation fee, distance etc. as input to calculate the scores and have utilized CoreNLP to process unstructured text.

Yu et al. [10] (2025) took forward the work in the domain by proposed Health-LLM, a retrieval-augmented disease prediction system. Their approach leverages large language models in conjunction with XGBoost and automated feature engineering for personalized recommendations. Data was of different types but GPT-4 was simply able to instruct on fitness instead. This was superior to the standard GPT-4 designs in clinical prediction tasks and this system embodies the next generation of predictive and adaptive healthcare AI.

Nayak et al. [11] (2023) presented a hybrid prototype for disease prediction and drug recommendation for intelligent healthcare using combination of several machine learning models. Their system integrates Decision Trees, Random Forests, Naive Bayes, and Support Vector Machines to improve the prediction accuracy and consistency. Through ensemble learning methods integrated with rich health database, the prototype not only predicts potential dis- ease but also recommends medication. The model showed superior accuracy and efficiency compared with single-model strategies, and these results suggest that multi-algorithmic fusion can benefit the development of intelligent and real-time clinical decision support systems.

Gupta et al. [12] (2021) proposed a machine learning-based computer assisted disease prediction and medicine recommendation system. They used the classification algorithm (decision trees and K-NN) to classify patient's symptoms and predict the possible disease and provide a recommendations of related drugs. Using structured data and symptoms mapping between diseases and drugs, the system offered a rule-based, but scalable methodology. This study showed the possibility of integration of classical classification methods to develop efficient simple decision support tools in medical practice.

Komal Kumar and Vigneswari [13] (2019) Developed drug recommendation for multidisease disease conditions in health care systems, representing patient checkup records are analyzed to identify different disease for machine learning. Their model used supervised learning techniques to compare patient information and recommend drugs to treat other conditions simultaneously. The strategy of the framework to tackle the issues of polypharmacy and personalized medicine was in line with a multi-disease treatment approach. This was a step towards incorporating reasoning over probabilistic belief into real-world healthcare problems, particularly for problems with overlapping features and treatments.

Okae et al. [14] designed a machine learning based end-to-end framework for dynamic disease management and drug recommendation directly from the learning perspective. They employed various models as Random Forest, SVM and Logistic Regression to predict the possible disease based on the symptoms entered and to suggest the medicine based on the symptoms entered. Its system had been designed from a user's perspective and benchmarked using a diverse set of datasets, achieving excellent prediction performance. This work emphasises on the need for ML-based solutions to play an even larger role in serving the scalability, and responsiveness of healthcare applications.

Mohapatra et al. [15] (2022) presented a machine learning method for drug recommendation to enhance clinical judgment. They took the patients' symptoms and health information as the input, and utilized the classification algorithm to realize disease prediction and medication selection. The system was designed to be highly interoperable and real-time and applicable to a point of care context. By focusing on the algorithms' efficiency as well as with regards to the physician's draft, the current study showed the potential of ML detools in the optimization of healthcare diagnostics and treatment planning.

Priya and Amuthaguka [16] (2024) gave a survey of machine learning based disease prediction approach including various algorithms, datasets and evaluation metrics that are normally used in the field. They compared techniques such as Decision Trees, Na¨ıve Bayes and Neural Networks, and compared their ability to predict the profile of a number of diseases from the paper. A good overview of the state-of-the-art and challenges were synthesised in this work, and it provided a good platform for future work in intelligent healthcare systems. In this review, we explore the roadmap to incorporate ML techniques into daily diagnostic practice.

Jin et al. [17] (2024), demonstrated Health-LLM, a personalized retrieval-augmented disease prediction system that utilizes large language models with machine learning to enhance diagnostic accuracy. Together with retrieval-augmented generation (RAG) on a model like XGBoost, this system could offer personalized predictions and recommendations taking patient-specific context into account. In baseline models Health-LLM performed better which supports that the strength of combination of both LLMs and structured learning model can be really significant in building intelligent healthcare AI system to AI enabled adaptive and context aware healthcare technology.

Yu et al. [18] (2024) promoted disease prediction with Health-LLM, a retrieval-augmented disease prediction model. Their answer is Neural networks + NLP with XGBoost and automated feature generation for personalized recommendations. Outperforming standard GPT-4 base models in clinical prediction during testing, this is a model of the future for intelligent and adaptive healthcare AI.

Mahalakshmi et al. [19] (2024) proposed, a cloud-based system includes real-time medical report analysis and AI-based diagnosis for real-time patient care support. Their approach combines natural language processing and machine-learning models to glean understanding from the unstructured medical language and produce diagnostic predictions. And it can be scaled up in a cloud-based deployment and available in real time, so it could be operational for a wide range of clinical scenarios. This study showcases AI and cloud technology that together are providing smart, data-driven healthcare services.

3 Methodology

3.1 Proposed Work

AI has had a great impact especially in healthcare and its use in automating Drug Recommendation. There are many works on the use of deep learning and natural language processing (NLP) for improving the accuracy of drug recommendations.

1) *Transformer-Based Models in Medical Text Processing:* The transformer pre-trained models like ClinicalBERT and BioBERT have demonstrated their capacity in extracting medical knowledge from EHRs. These models, instead, enhance diagnosis and treatment suggestions through the interpretation of complicated medical terms.

2) *Deep Learning for Drug Recommendation:* Recently, researchers applied deep learning model to predict drug recommendations from patient data. They combine demographic and medical history information, with symptoms to give more personalized medication guidance.

3) *Knowledge Graphs in Healthcare:* Some authors have involved knowledge graphs to

improve recommendation accuracy. Such systems relate diseases, symptoms, and drugs and offer a more structured way to recommend drugs.

4) *Evolution of Clinical Decision Support Systems (CDSS):* Traditional CDSS were based on rule-based or probabilistic approached, whereas AI-based models are currently more flexible and accurate. Deep learning has led to improved quality of patient-specific treatment plans in these systems.

5) **3.2 Flow Graph**

The flow diagram in Fig. 1 shows the systematic methodology for drug recommendation with AI. First, medical records including patient information, diagnosis, and drug advice are compiled. This raw data is pre- processed and used to deal with missing values, eliminate inconsistencies, and normalize the dataset to help the model to perform better. After cleaning, and pre-processing, the dataset is divided into training and testing datasets to create and test the model. We then train a transformer-based NLP model, ClinicalBERT, on the processed data to capture complicated interactions between patient characteristics and recommended medications. After training, the model is deployed to a user-friendly interface where users can input parameters such as age, gender, and diagnosis. The system then recommends the most suitable drug, along with its dosage, route of administration, frequency, duration, and medical indication. This AI-powered approach ensures personalized and data-driven medication recommendations, improving recommendation accuracy and enhancing patient outcomes.

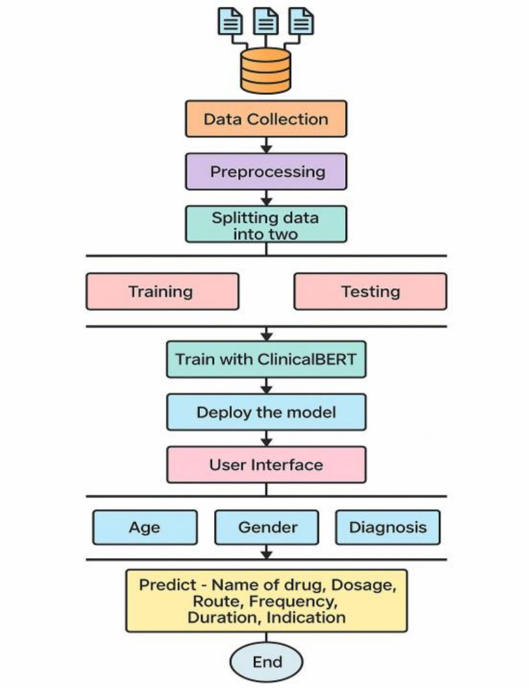

Fig. 1. Proposed Flow Graph.

3.3 Architecture

The ClinicalBERT architecture is designed to recommend essential medical recommendations based on age, gender, and disease. These input features are first converted into token em- beddings, which represent them in a format suitable for deep learning models. To capture sequential relationships, positional encoding is applied, ensuring that the model understands the order of inputs.

In Fig.2 the data is processed through an N-layer Trans- former Encoder, which consists of multi-head attention for contextual understanding and feed-forward layers for learning complex patterns. The [CLS] token aggregates the encoded information, enabling the model to predict key medical pa- rameters such as drug name, dosage, administration route, frequency, and duration. This structured approach allow ClinicalBERT to provide accurate and context-aware drug recommendations.

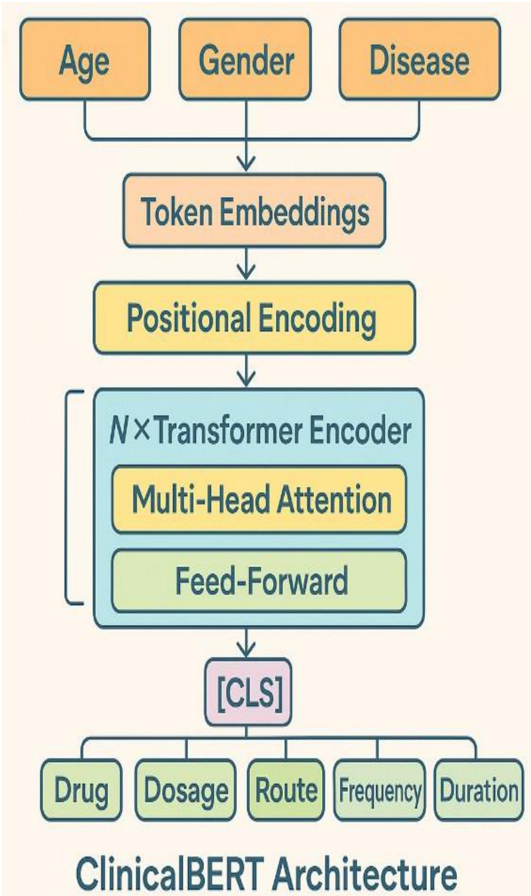

Fig. 2. Proposed Model Architecture.

3.4 Dataset Collection

We collected our dataset in the first instant from Kaggle, which gave us a structured CSV file of 1000 rows and 10 columns. The dataset contains vital patient information including age and sex, and comorbidity findings and is formulated to predict the different components with respect to drug recommendation that are namely drug name, dose, duration of administration, frequency, administered route, and reason for administration. In order to augment the data for better training our AI model, we increased the dataset with diverse patient records from 1000 to 2000 rows. This extension can increase generalization, as the data set is more diverse. The Table-1 shows the attributes type of dataset and descriptions of the attributes respectively. In addition, data consistency was kept and bias was reduced by adjusting for either age groups, or sex and disease types. Imputation methods were used to deal with missing values, and the model was never influenced. Therefore, the enhanced dataset provides a strong basis for the successful training and validation of our deep learning models.

3.5 Data Preprocessing

Data preprocessing serves as the foundation for accurate drug recommendation, which involves crucial steps such as data cleaning, transformation, and structuring of raw medical data. By optimizing the dataset, the machine learning model, specifically ClinicalBERT, can efficiently analyze patient attributes and uncover significant patterns between diagnoses and recommended medications. This preprocessing step enhances the model's ability to generate precise recommendations regarding drug selection, dosage, administration route, frequency, and duration, ultimately contributing to improved clinical decision-making and patient care.

Table 1. Description of Medical Recommendation Dataset

Name	**Type**	**Description**
Age	Int	Patient's age
Gender	String	Patient's gender
Diagnosis	String	Medical conditions diagnosed
Name of Drug	String	Name of the recommended drug
Dosage (gram)	Float	Dosage amount in grams
Route	String	Method of drug administration
Frequency	String	How often the drug should be taken
Duration (days)	Int	Number of days
Indication	String	Medical reason for precommending the drug

3.6 Feature Extraction

Feature extraction simplifies complex medical data by iden- tifying and transforming the most relevant information for analysis. In this process, essential characteristics such as age, gender, and diagnosis are selected to ensure accurate drug recommendations. To maintain the efficiency of the model, 20% of the original dataset is reserved for testing, allowing the model to generalize well on unseen data as shown in fig.3. The model achieved a training accuracy of 96.5% and a test accuracy of 91.3%, demonstrating strong performance and reliability in real-world prediction scenarios.

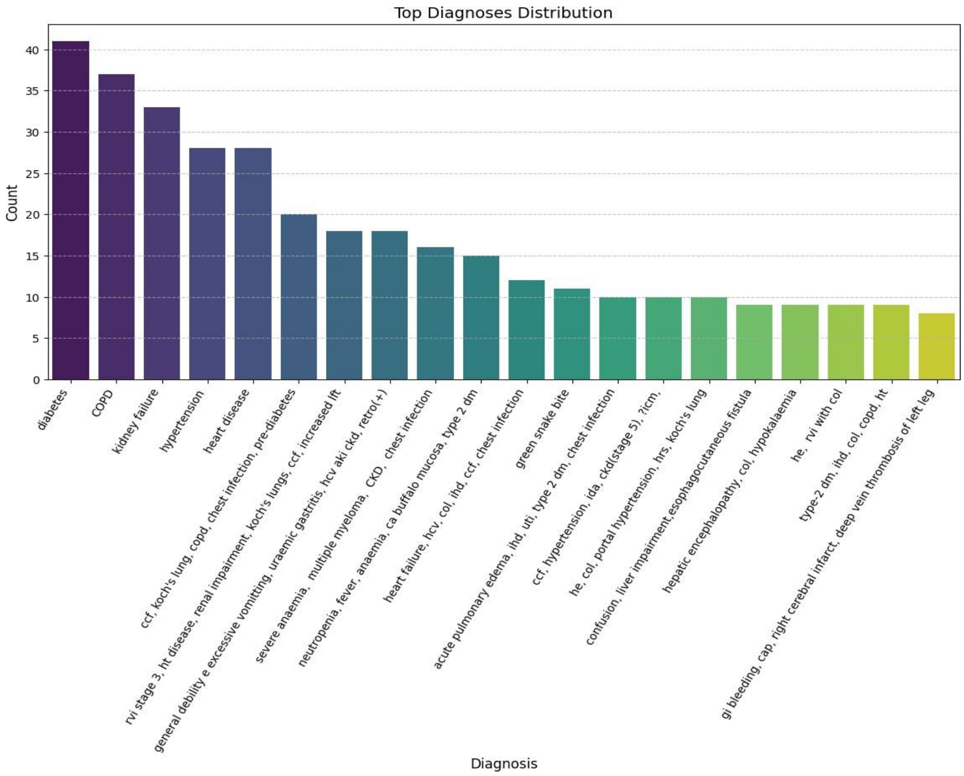

Fig. 3. Diagnosis Distribution.

4 Results Analysis And Comparison Study

Our output will be a user interface where the user should enter their age, gender and diagnosis, from the given data the prescription prediction of name of drug, dosage, duration, frequency, route and Indication.

4.1 Comparative Analysis

The Fig. 4 bar chart compares the accuracy of various models in drug recommendation. Traditional models like Logistic Regression, Random Forest, XGBoost, KNN, Decision Tree, and SVC achieved around 94.72%, with Decision Tree slightly higher at 94.85%, while Na¨ıve Bayes recorded the lowest at 94.38% due to its independent feature assumption. In contrast, ClinicalBERT significantly outperformed all models with 97.5% accuracy and a

96.85% cross-validation score, demonstrating the superiority of transformer-based models in handling structured medical data, as shown in Table 2.

Table 2. Comparison of Different Algorithms with Accuracy and Cross-Validation Scores.

Sr. No	Algorithms	Accuracy Score	Cross Value Score
1	Logistic Regression	94.72	95.1
2	Random Forest	94.72	95.1
3	XGB Classifier	94.72	95.1
4	KNN Classifier	94.85	94.7
5	Decision Tree	94.72	95.1
6	Na¨ıve Bayes	94.38	95.1
7	SVC	94.72	93.82
8	**ClinicalBERT (Proposed Model)**	**97.5**	**96.85**

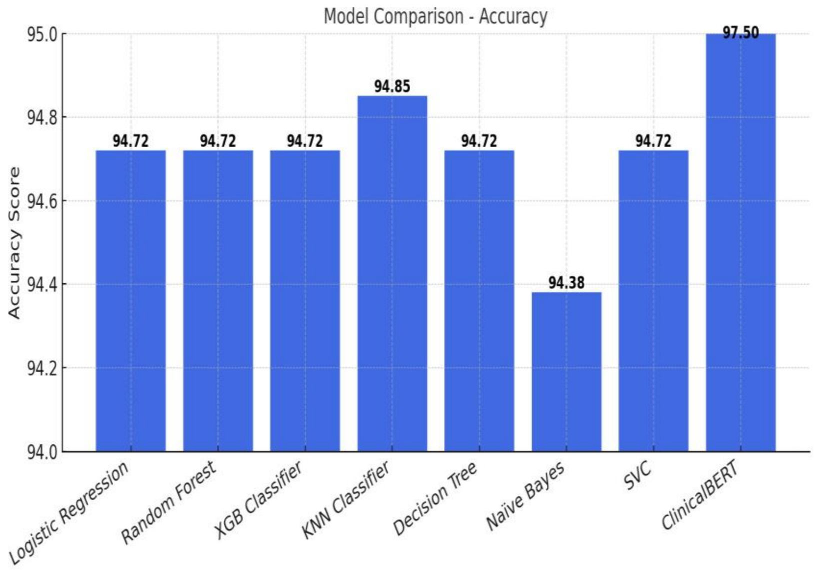

Fig. 4. Comparative Analysis Graph.

4.2 User Interface

Fig.5 represents the DeepMed drug recommendor is an AI-powered tool designed to assist in drug recommendation by analyzing patient details. Users provide their age, gen- der, and medical diagnosis, which the system processes to generate a recommended prescription. By leveraging ClinicalBERT, the model ensures precise medication suggestions based on medical records and AI-driven analysis. Clicking the ”Predict” button, the system outputs critical recommendation details, including the drug name, dosage, administration route, frequency, duration, and medical indication. This approach enhances clinical decision-making by providing AI-generated recommendations tailored to patient-specific conditions.

4.3 Confusion Matrix

The Confusion Matrix in Fig.6 represents the performance of the DeepMed recommendations across all possible labels in the dataset. Each axis corresponds to true labels (actual values) and predicted labels (model outputs), providing insights into classification accuracy. Cell intensity represents frequency of recommendation, the diagonal corresponds to a correct classification. The off-diagonal elements emphasize misclassifications, enabling us to investigate error patterns. The data contains several drug recommendations, dosages, administration routes, frequency, duration, and medical indications, and this heat matrix visualizes how the model will generalize between these classes.

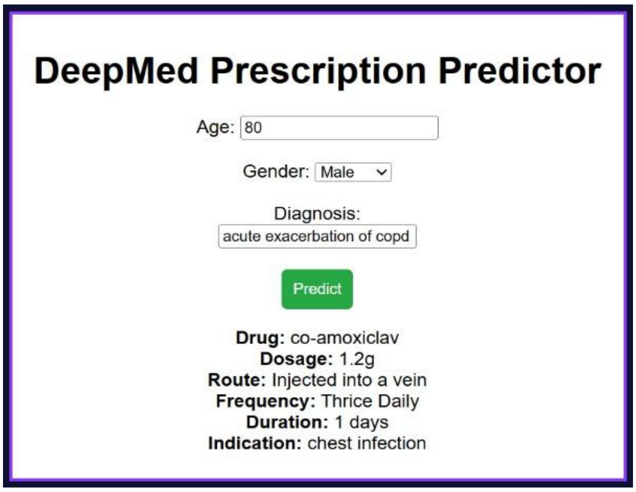

Fig. 5. User Interface.

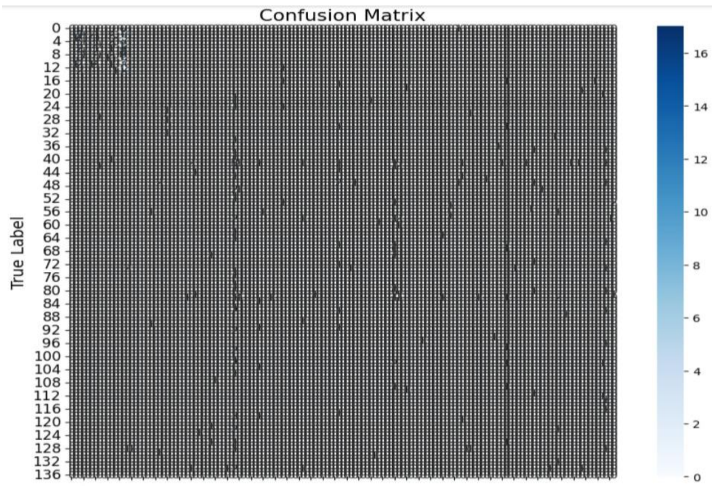

Fig. 6. Confusion Matrix.

5 Conclusion

In summary, our AI-powered drug recommendation sys- tem is aimed to make medical decision-making smarter and efficient. Through meticulous data cleaning and organization, the model can predict with high accuracy the correct drug, dosage, route, frequency, duration, and indication given a patient's individual details. By using advanced deep learning and more specifically, ClinicalBERT, the model intuitively "knows" the complex medical patterns and becomes a useful tool in the hands of healthcare professionals. Not only does it decrease the possibility of recommendation errors, but also confirmation leads to personalized treatments, which improves patients' health and the care system.

This work provides an in-depth investigation of medical recommendation based on state-of-the-art machine learning methods which could offer potential superb accuracy and high efficiency in the medical decision-making process. Furthermore, clinicalBERT improves context-aware and more accurate recommendations. Selecting, cleaning and optimizing both the models and data were essential to produce useful results. Experimental study indicates that an outstanding improvement for recommendation accuracy can be achieved, showing it's prospective in real world applications. Nevertheless, there are several issues, such as data imbalance and interpretability that still have potential for their further development. The research suggests that AI may play an important role in medical decision-making, for fewer errors and better long-term patient care. Additional study can improve prediction models using a larger variety of datasets along with explainable AI methods. In sum, our results enrich the literature on AI-based healthcare with promising

Future developments could develop to incorporate Real-time patient data and federated learning to improve privacy and security. Furthermore, increasing the dataset to include diversity in socio-demographics and geography could enhance generalizability of the model. To cope with such interpretability issue by utilizing explainable AI (XAI) methods, which help to establish the confidence of medical professionals towards the robust and transparent decision. Ultimately, the use of AI-generated insights has the potential to transform personalized medicine, leading to better treatment regimens and patient outcomes at a grand scale.

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