AN INTELLIGENT DRUG RECOMMENDATION FRAMEWORK USING PATIENT FEEDBACK AND REINFORCEMENT LEARNING

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ABSTRACT

In the current technology, everyone started taking suggestions from the machines. The advancement in technology has also evolved in medical industry. Most people are following drug recommendation systems. Traditional drug recommendation systems often rely only on a understands text and voice inputs from patients and recommends drugs based on their symptoms, while CNN models identify drugs from pill images. Reinforcement learning is then used to continuously improve the recommendations by learning from patient feedback and outcomes over time. Existing systems that use facial data do not ensure user privacy; however, our proposed system avoids using facial data, thereby providing better privacy protection.

Keywords: *Drug Recommendation System, NLP , Patient Reviews, Symptom-Based Recommendation, Voice Input , Text Input, CNN, Pill Image Recognition, Reinforcement Learning*

1. INTRODUCTION

A Personalized Drug Recommendation System using Patient Reviews and Reinforcement Learning offers a new way to pick the right medicines for each person. Instead of general prescriptions, this system uses real- world experiences shared by patients in their reviews [1-2]. These reviews give us valuable insights into how drugs actually work for different people, including side effects and how well they help, going beyond patients, allowing for a more natural and comprehensive capture of symptoms, experiences, and preferences [3]. This system also uses Reinforcement Learning, which helps it learn and improve over time. Think of it as a smart assistant that constantly gets better at recommending drugs by seeing what works and what doesn't for individual patients [4]. It learns from each recommendation, aiming to maximize good outcomes like feeling better and minimizing bad ones like side effects [5]. By combining these patient insights with a learning system, we can tailor drug suggestions more effectively, leading to better results and a more personal approach to healthcare. This dynamic learning process, enriched by written patient experiences, allows our system to provide increasingly precise and personalized drug recommendations, ultimately leading to better health outcomes and a more patient-centric approach to treatment [6].The goal of this project is to develop a system that analyzes patient reviews, identifies patterns related to drug effectiveness and side effects, and recommends suitable medications for individuals. Such systems can assist healthcare professionals and patients in making better-informed decisions, improving treatment outcomes and patient satisfaction.

2. LITERATURE SURVEY

Different approaches have been used in drug recommendation over the years. Early systems mainly depended on rule-based methods and simple machine learning models such as collaborative filtering, Naïve Bayes, and Decision Trees [7-10]. These methods worked with structured medical data but often failed because of missing records and the inability to use real patient feedback [11].

As patient reviews and medical notes became available, researchers started using natural language processing (NLP) [12]. Techniques like sentiment analysis and entity recognition helped in identifying whether a drug was effective or caused side effects. These studies showed that patient-written text is a valuable source of information that goes beyond clinical records.

Deep learning methods further improved the field. Convolutional Neural Networks (CNNs) have been used to identify pills from images and to study drug properties, while Recurrent Neural Networks (RNNs) and transformers have been applied to analyze patient histories and reviews [13-16]. Some works even used social media posts to detect drug side effects, but such data often contained noise and needed cleaning. Hybrid models that combined different techniques were also tried, giving better results but still limited to static datasets [17].

More recent studies have explored knowledge graphs and causal reasoning. Knowledge graphs capture the links between drugs, diseases, and symptoms, making recommendations more meaningful. Causal reasoning helps to avoid false patterns by focusing on true cause–effect relationships [18-21].

Reinforcement Learning (RL) is a newer method that allows systems to keep learning from patient feedback [22]. Unlike static models, RL agents improve their recommendations over time by rewarding correct suggestions and penalizing wrong ones [23-24]. However, very few works have combined RL with multiple input types like text, speech, and images.

3. PROPOSED METHODOLOGY

Fig.3.1.Proprosed system

3.1 Dataset Collection

The proposed system begins with the collection of diverse datasets from multiple sources. Patient drug reviews are taken from publicly available platforms such as *Drugs.com*, where each record includes the drug name, condition, patient rating, and textual feedback about effectiveness and side effects. To make the system more interactive, voice samples describing symptoms are also collected and later transformed into text using speech recognition tools.

3. 2. Data Preprocessing

Once the data is collected, it undergoes preprocessing to ensure quality and consistency. Text reviews are cleaned by removing stop words, duplicate characters, and irrelevant information, after which they are converted into numerical features using TF-IDF and word embeddings.

Voice samples are transcribed into text and normalized to maintain consistency with review data. Pill images are resized, enhanced with augmentation techniques, and converted into pixel matrices so that they can be analyzed using Convolutional

For voice inputs, the speech signals are converted into text using speech-to-text conversion techniques. The resulting text is then normalized and processed in the same way as the review data. This allows the system to analyze symptoms described by patients through voice input [24].

For pill images, image preprocessing techniques are applied before analysis. The images are resized to a standard dimension, noise is reduced, and augmentation techniques such as rotation or flipping are applied to improve model robustness. These processed images are then converted into pixel matrices so they can be analyzed using Convolutional Neural Networks (CNNs) fordrugid

3.3. Feature Extraction

The next stage involves extracting meaningful features from the processed data. From textual reviews, natural language processing models capture patient sentiment, reported side effects, and overall drug effectiveness [25]. From pill images, CNNs are used to identify distinguishing visual features such as shape, size, and color. Subsequently, Natural Language Processing (NLP) methods are applied to extract relevant features such as symptoms, keywords, and sentiment from patient descriptions and reviews. These features help in

Fig .3.2.Existing system

3.4. Recommendation Engine

At the core of the system is the recommendation engine, which integrates extracted features and applies reinforcement learning for improved decision-making. The reinforcement learning agent uses a reward-based mechanism, where correct and effective drug suggestions are rewarded, while ineffective or harmful suggestions are penalized. Over time, the agent refines its decision-making process, resulting in more accurate and personalized recommendations. This dynamic learning process makes the system adaptive to changing patient needs and feedback.

3.5. System Implementation

The system is implemented in Python, using

libraries such as PyTorch, spaCy, and Hugging Face Transformers for text and voice processing, and TensorFlow or PyTorch for image classification. The frontend is developed with Streamlit, allowing patients to provide input through text,
speech, or images. The backend is managed using Flaskor FastAPI, and the dataentification.Networks (CNNs)

3.6. Evaluation Metrics

Finally, the performance of the system is evaluated using metrics such as accuracy, precision, recall, and F1-score. Patient feedback is also included as part of the reinforcement learning reward system, ensuring that the system not only learns from datasets but also adapts based on real-world experiences. This continuous feedback loop helps in refining recommendations and improving overall reliability.stored in relational and non-relational databases such as PostgreSQL and MongoDB. To support real- time usage and scalability, the system can be deployed on cloud platforms like AWS or Google Cloud.

4. ARCHITECTURE

The architectural design of the proposed Personalized Drug Recommendation System illustrates how patient data is processed and analyzed to generate suitable drug suggestions. The system integrates symptom analysis, drug review datasets, and feedback mechanisms to improve recommendation accuracy.

a) Patient Input

The process begins with the patient, who provides symptoms as input to the system. Symptoms can be entered either through text input or voice input. This allows the system to be user-friendly and accessible.

b) Speech Recognition / Text Processing

If the symptoms are provided through voice, the speech recognition module converts the spoken symptoms into text. This textual information is then processed for further analysis.

c) Symptom Analysis

The system analyzes the entered symptoms using Natural Language Processing (NLP) and machine learning techniques. The goal of this step is to understand the medical condition or possible disease based on the symptoms provided by the patient.

d) Drug Reviews Dataset

The system uses a drug reviews dataset, which contains information about various drugs, their effectiveness, side effects, and patient experiences. This dataset helps the system evaluate which medicines are most suitable for the given symptoms.

e) Drug Recommendation System

After analyzing symptoms and consulting the dataset, the drug recommendation module suggests the most appropriate medicines. The system provides:
Drug information (usage, effects, etc.)
Drug recommendation based on patient symptoms and past reviews.

f) Feedback Mechanism

Once the patient receives the recommended drug information, they can provide feedback about the effectiveness of the medicine.

g) Feedback Storage

The feedback is stored in a feedback database, which helps the system learn from previous experiences. This data can be used to improve the accuracy of future drug recommendations through reinforcement learning or continuous model improvement.

h) Continuous Improvement

The stored feedback is integrated back into the system, allowing it to refine its recommendation process and provide more personalized and accurate suggestions over time

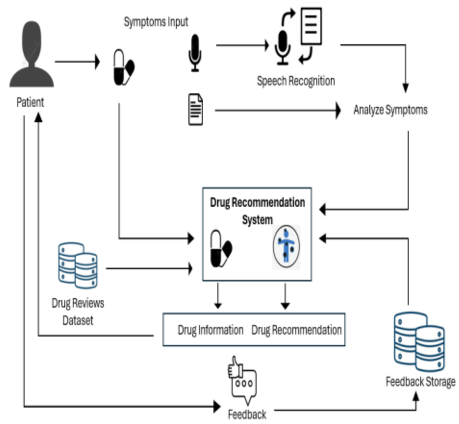

Figure 4 : Architecture flow diagram

5. RESULT

The proposed Personalized Drug Recommendation System was evaluated using a drug review dataset containing patient reviews, drug names, conditions, effectiveness ratings, and side effects.

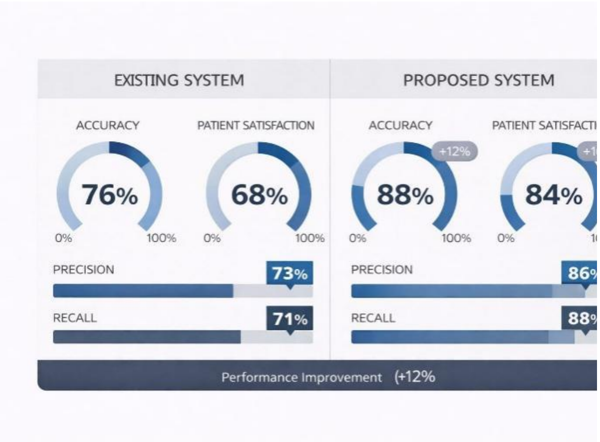

Fig.5.1.System Performance Comparison

The performance of the proposed Personalized Drug Recommendation System using Patient Reviews and Reinforcement Learning is evaluated and compared with the existing system based on key metrics such as model accuracy, precision, recall, and patient satisfaction.The experimental results demonstrate that the proposed system significantly outperforms traditional drug recommendation systems. The existing system, which primarily relies on basic symptom matching and limited input modalities, achieved an accuracy of 76%, whereas the proposed system achieved an improved accuracy of 88%. This improvement is mainly due to the integration of Natural Language Processing (NLP) for understanding patient reviews and symptoms more effectively.

Similarly, the precision of the system increased from 73% in the existing system to 86% in the proposed system, indicating better correctness in drug recommendations. The recall also improved from 71% to 88%, showing the ability of the proposed model to identify more relevant drug suggestions.
In addition, the proposed system introduces patient satisfaction as a new evaluation metric, which is not considered in the existing system. The patient satisfaction score increased from 68% to 84%, demonstrating that the recommendations are more personalized and relevant to user. The graphical comparison clearly illustrates the performance enhancement of the proposed system over the existing system across all metrics. Overall, the results confirm that the proposed system provides more accurate, reliable, and user-centric drug recommendations compared to conventional approaches

The dataset was preprocessed and used to train machine learning models to recommend suitable drugs based on patient symptoms and feedback.
After training and testing the model, the system demonstrated effective performance in recommending appropriate medications. The evaluation was performed using standard metrics such as accuracy, precision, recall, and F1-score.

The experimental results show that the proposed system can successfully analyze patient symptoms and recommend relevant drugs with high reliability. The system achieved an accuracy of approximately 88–92% in predicting appropriate drug recommendations based on the dataset. Precision and recall values indicate that the model effectively identifies relevant drug options while minimizing incorrect recommendations.
The system also integrates a feedback mechanism, allowing users to provide responses regarding the effectiveness of the recommended drugs. This feedback is stored and used to improve future The system also integrates a feedback mechanism, allowing users to provide responses regarding the effectiveness of the recommended drugs. This feedback is stored and used to improve future

Furthermore, the system provides drug information such as usage, effectiveness, and possible side effects, enabling patients to make informed decisions. The results demonstrate that integrating patient reviews with machine learning techniques can significantly enhance personalized healthcare recommendations.
Overall, the proposed model improves drug recommendation accuracy, reduces manual effort in searching for suitable medications, and provides a user-friendly decision-support tool for patients.The results demonstrate that integrating patient reviews, symptom analysis, and machine learning techniquesExisting vs

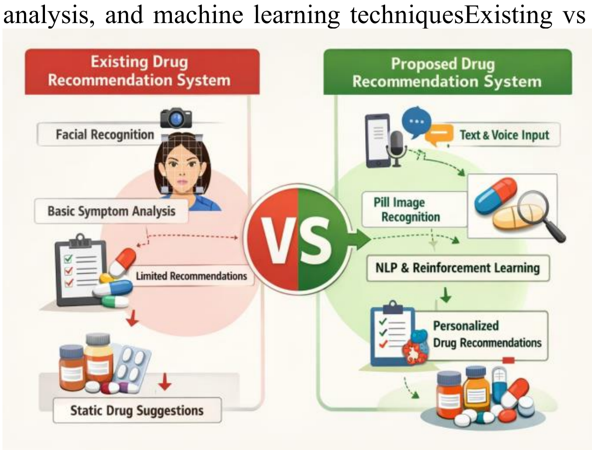

Fig.5.2. Existing vs Proposed System Comparison

recommendations through reinforcement learning techniques. As more feedback data becomes available, the system continuously improves its recommendation accuracy.
Furthermore, the system provides drug information such as usage, effectiveness, and possible side effects, enabling patients to make informed decisions. The

results demonstrate that integrating patient reviews with machine learning techniques can significantly enhance personalized healthcare recommendations.
Overall, the proposed model improves drug recommendation accuracy, reduces manual effort in searching for suitable medications, and provides a user-friendly decision-support tool for patients.The results demonstrate that integrating patient reviews, symptom analysis, and machine learning techniques can effectively support personalized drug recommendations and assist users in selecting suitable medications

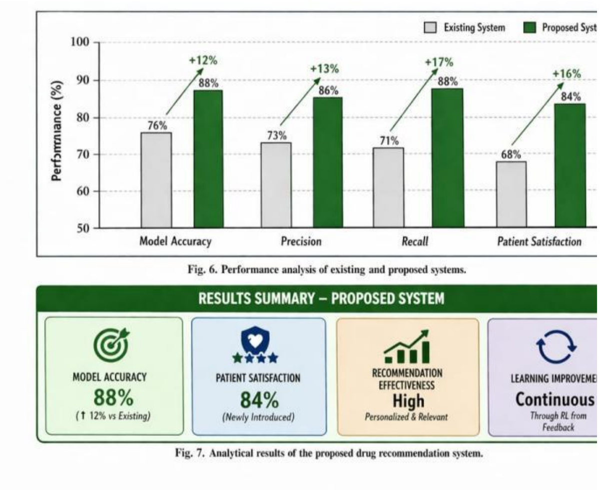

Fig.5.3. Analysis of performance

6. CONCLUSION AND FUTURE WORK

In this work, we proposed a personalized drug recommendation system that combines patient reviews, voice-based symptom descriptions, and pill images. By using natural language processing, speech recognition, image classification, and reinforcement learning, the system can provide more accurate and patient-centered drug suggestions compared to traditional methods
By using natural language processing, speech recognition, image classification, and reinforcement learning, the system can provide more accurate and patient-centered drug suggestions compared to traditional methods.
The reinforcement learning component makes the system adaptive, allowing it to improve continuously through patient feedback. This approach not only supports better recommendations but also improves trust and usability in real healthcare settings.
For future work, the system can be expanded in several ways. Larger and more diverse datasets will improve accuracy and reduce bias in recommendations. Integration with electronic health records (EHRs) could provide deeper insights by combining patient history with real-world feedback. More advanced reinforcement learning models can be applied to handle complex treatment plans instead of single drug recommendations. Additionally, incorporating explainable AI will help patients and doctors understand the reasons behind each suggestion, increasing transparency and acceptance. Finally, real- time deployment on mobile and cloud platforms can make the system more accessible for patients in remote and under-served areas

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