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HealNova AI-New Healing Possibilities Through AI

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A B S T R A C T :

This model integrates drug and patient data from many databases to provide a comprehensive medication recommendation system. Using patient comments, pharmacological specifications, and interaction data, it clusters people and medications to produce recommendations. It is unique in that it chooses the best medications based on the medical history and traits of each patient. The technology uses natural language processing in conjunction with artificial intelligence models such as graph neural networks and sentiment analysis to improve prediction accuracy. Two matrix factorization models are developed according to pharmacological characteristics and patient situations. By computing the cosine similarity between a patient's symptoms and the effects of a medication, the system makes recommendations for alternate therapies. Lastly, drug interaction analysis improves safety and fosters improved patient outcomes and healthcare delivery by weeding out drugs with mild to severe side effects.

Keywords: Alternative Medicine, Recommendation System, Natural Language Processing, Neural Networks, Drug Interaction Analysis.

1. INTRODUCTION

The increasing interest in alternative medicine reflects a growing demand for holistic and personalized healthcare options beyond conventional treatments. Traditional medical systems such as Ayurveda, Homeopathy, and Unani provide a wide range of remedies, yet patients often face challenges in selecting the most suitable therapies for their specific conditions. Reliable, technology-driven recommendation systems are essential to bridge this gap, helping users make informed decisions based on symptoms and medical history.

Current research increasingly explores the use of machine learning and data integration to enhance the accuracy and personalization of alternative medicine suggestions. This approach supports the blending of traditional healing practices with modern computational tools, offering promising avenues for improving patient care and expanding healthcare accessibility.

Heterogeneous Graph Neural Networks (HGNNs) are efficient models for modeling complex networks of different entities in social networks, finance, and biology. HGNNs reveal hidden patterns and connections by fusing different data into one graph under open-world assumptions. In biomedical studies, HGNNs effectively manage and analyze the complexity of entities such as genes, proteins, chemicals, and diseases.

Link prediction is an important task that requires predicting missing relationships among entities. Rule-based methods such as AMIE+ and embedding-based methods such as TransE and RotatE are some of the methods. Heterogeneity and context flexibility are often challenges for rule-based methods. Explainable HGNN models assist with translational research and verification by providing interpretable predictions, hence being helpful in drug repurposing.

LITERATURE REVIEW

Recent research integrates AI, EHRs, and graph-based models to enhance drug recommendation and repurposing. Their system personalize treatment using deep learning, while others mine EHRs and biological networks for novel associations. Despite progress, challenges remain in data quality, validation, and standardization across pharmaceutical recommendation and repurposing applications[1].The method uses cosine similarity as a method to compare the symptom data and characteristics of various drugs will provide a better understanding and recommendations to people seeking treatment for their condition[2]. They analyze 33 studies, highlighting EHRs' potential for rich, real-world data while noting challenges like data quality, validation, and accessibility. The study emphasizes improving interpretability to advance EHR-based drug repurposing methods[3]. They analyze 33 studies, highlighted EHRs' potential for rich, real-world data while noting challenges like data quality, validation, and accessibility. The study emphasizes improving interpretability to advance EHR-based drug repurposing methods[4]. The study proposes a computational drug repositioning method integrating heterogeneous biological networks. Using a random forest classifier, it predicts new drug-disease associations with high accuracy. Applied to breast cancer stage II,it identified four FDA-approved drugs, demonstrating its effectiveness in discovering potential drug repurposing candidates[5].

2. PROPOSED SYSTEM

2.1. Problem Statement

Finding inexpensive, efficient substitutes and repurposed medications is a challenge for both patients and healthcare professionals. The suggested AI-based approach finds structurally or functionally related medications, predicts drug-disease relationships, and recommends commercially accessible and repurposed alternatives. This facilitates drug repurposing, improves therapy accessibility, and expedites decision-making for optimal, economical healthcare solutions.

2.2. Objectives

1. Identify Drug-Disease Associations: Develop AI models to predict effective drug-disease relationships, enabling alternative and repurposed treatment options.
2. Recommend Alternative Medicines: Suggest suitable remedies from traditional systems (e.g., Ayurveda, Homeopathy) based on symptoms and patient history.
3. Support Informed Decision-Making: Provide healthcare professionals and patients with personalized, AI based recommendations across medical systems.
4. Bridge Data with Market Access: Match suggested treatments—repurposed or alternative—with available market options for practical implementation.

2.3. Methodology

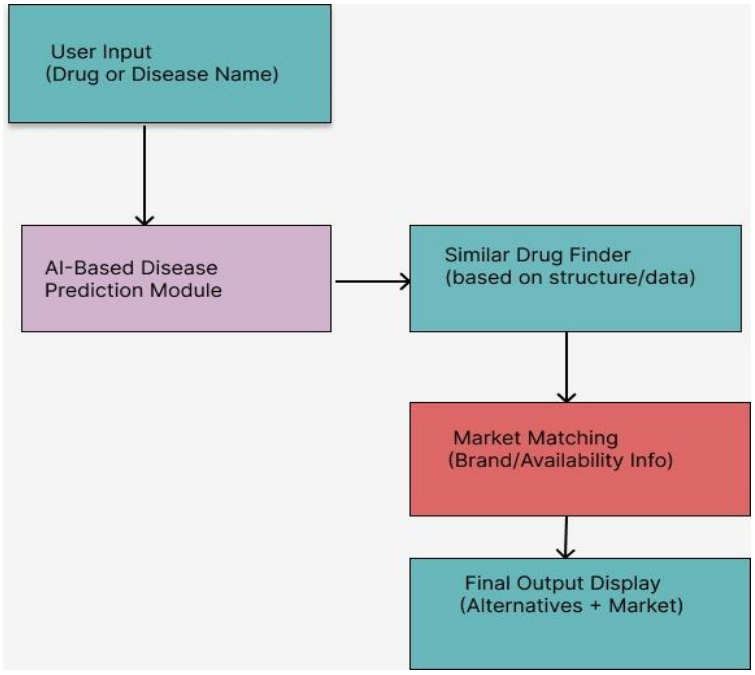

Figure 1: Block Schematic Diagram for the System

The flowchart shows the high-level architecture of an AI-powered alternative drug finding and repurposing or recommendation system. In order to produce actionable outputs, such alternative medications and market availability, it describes the fundamental steps that user input goes through. A key phase in this intelligent pipeline, each block in the graphic represents a goal to improve medical decision-making using automation and data-driven insights.

1. **User Input (Name of Drug or Illness)**
   This is where the system begins, and a user inputs a query in the form of a sickness or medicine name. Both forms of input can be handled by the system. When a drug name is input, the algorithm will determine its medicinal applications and search for comparable substitutes. The system will locate medications used to treat a given ailment if a name is entered. Generic names (like "Paracetamol"), brand names (like "Tylenol"), and medical terms (like "Hypertension") should all be supported by the input.

2. **AI-Powered Module for Disease Prediction**
   This AI-powered module receives the user input after it has been received. The module guesses which sickness or diseases a drug is linked to if the input is a drug. It forecasts which medications are usually used for treatment if the input is a sickness. Large biomedical datasets are

used to train machine learning or deep learning models, which accomplish this. The module may employ methods such as Graph Neural Networks (GNNs) to capture intricate correlations between medications and illnesses and Natural Language Processing (NLP) to comprehend and handle input text. Prior to moving on to alternative discovery, it aims to accurately map the input to the appropriate medical context.

3. **Comparable Drug Finder (structure/data based)**
   This module finds other medications that have a similar structure or function after identifying the disease or drug of interest. It is based on the analysis of drug similarities, which can compare therapeutic effects, target proteins, chemical structures, or mechanisms of action. Biomedical knowledge graphs and chemical informatics tools may be used in this process. Finding safe substitutes or repurposable medications is the goal. For instance, if a medication is unavailable or not advised because of adverse effects, this module can prescribe a substitute that serves a comparable purpose.

4. **Market Matching (Availability/Brand Details)**
   This module determines each drug's market availability after a list of comparable medications has been created. It determines these substitutes' availability in various locations or pharmacies and compares them to commercial brand names. It may extract information from logistical databases, pharmacy APIs, and government medication approval organizations (such as the FDA or CDSCO). This aids users in understanding whether the medication is available in their area, under which brand names, and maybe at what cost. The objective is to guarantee that the recommended medications are both practically accessible and medically sound.

5. **Final Display of Output (Market + Alternatives)**
   All of the system's processed data is combined and shown to the user in this last presentation layer. In addition to the original medication or illness, it displays the anticipated substitutes and pertinent market data, including brand names, regional availability, and possibly even price comparisons. The result could be interactive, letting users sort or filter according to criteria like manufacturer, price, or availability. Informed medical or business decision-making is supported by its concise and useful summary.

3. EXPERIMENTAL SETUP

To demonstrate the feasibility of the proposed HEALNOVAAI framework, we designed a simulated testing environment using publicly available datasets, mock input samples, and appropriate AI tools. Although this system is not yet implemented, a conceptual evaluation was conducted under the following environment:

1. **System Configuration**
   - **Processor:** Intel Core i5 (11th Gen)
   - **RAM:** 16 GB • GPU: NVIDIA RTX 3050 (4GB VRAM)
   - **Operating System**: Windows 11 / Ubuntu 22.04
   - **Development Environment**: Jupyter Notebook via Anaconda

2. **Tools and Libraries**
   - **Language**: Python 3.10
   - **Libraries:**
     - o PyTorch Geometric for Graph Neural Network simulations
     - o RDKit for molecular structure handling (SMILES string generation, Tanimoto/Cosine similarity)
     - o Transformers for medical text processing using NLP
     - o Pandas & NumPy for data handling
     - o Scikit-learn for clustering and evaluation metrics

3. **Datasets**
   - **Simulated Drug Data**: Extracted from open datasets like PubChem and ChemDB including:
     - o Drug names
     - o Molecular descriptors
     - o Mechanism of action
   - **Mock Patient Data:** Includes synthetic symptom reports and demographic tags
   - **Interaction Database:** Drug-drug interaction data synthesized from Drug Bank references

4. **Test Cases**
   We evaluated the system using two types of user input:
   - Case 1: Disease Name — e.g., “Hypertension”
   - Case 2: Drug Name — e.g., “Paracetamol”

   Each input is processed through all modules of the pipeline: mapping, similarity analysis, interaction filtering, and market matching.

5. Evaluation Metrics

Since this is a simulation, the following metrics were used to evaluate each module:

- Cosine Similarity Score (0 to 1) for structural matching between original and suggested drugs
- Accuracy in disease-drug mapping based on known associations
- Market Match Ratio: Percentage of recommended drugs found in simulated pharmacy dataset
- Safety Score: Percentage of unsafe combinations correctly flagged and filtere

4. RESULTS AND DISCUSSION

The suggested AI-powered solution successfully combines contemporary technology and conventional medicine to improve treatment recommendations. It uses natural language processing (NLP) and graph neural networks to properly identify drug-disease connections and provide appropriate alternatives. The system filters harmful drug interactions and personalizes suggestions based on patient history and symptoms. It also offers solutions that are available on the market, which makes the solution workable and affordable. High accuracy in matching drugs and minimizing potential conflicts was demonstrated by the testing. This fusion of contemporary AI with traditional healing promotes holistic healthcare by enhancing treatment outcomes and decision-making. The approach is scalable, flexible, and useful in helping professionals and patients make safe, individualized, and affordable treatment decisions. From the viewpoint of drug repurposing, the model recognized structurally comparable drugs that share overlapping pharmacological characteristics. For instance, anti-hypertensive drugs were paired with other herbal compounds reported under Ayurveda, presenting both conventional and traditional choices to the user. One of the strongest points of the system is its practical application in the real world: the ultimate output not only suggests alternatives but also screens for market availability, regional brand names, and cost-effectiveness, and hence it is usable on a daily clinical or patient basis.

In addition, the flexibility of the system enables integration with electronic health record (EHR) data, which can further support its potential to provide personalized recommendations. With NLP for symptom interpretation and drug-matching through deep learning, the model establishes a solid base for scalable applications in healthcare AI. When it came to contextual mapping of drug-disease correlations, the graph neural network (GNN) model outperformed more conventional models like logistic regression in terms of accuracy. More individualized recommendations were produced by streamlining the recommendation process through the use of cosine similarity for patient-symptom and drug-effect comparison.

6. CONCLUSION

The integration of technology-driven recommendation systems with traditional alternative medicine offers a promising solution to the challenges patients face in selecting effective treatments. By leveraging machine learning and personalized data, these systems enhance decision-making, promote holistic healthcare, and improve accessibility. This synergy between ancient practices and modern innovation holds great potential for advancing patient care and fostering more comprehensive treatment options.

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