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SURVEY ON INTELLIGENT DISEASE PREDICTION AND DRUG RECOMMENDATION USING MACHINE LEARNING ALGORITHMS

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ABSTRACT

The integration of machine learning (ML) in healthcare, especially in disease prediction and drug recommendation, has revolutionized medical decision-making. This literature survey consolidates the key methodologies, models, and technological progress made by various researchers. Drawing on over 15 significant studies between 2012 and 2023, the review explores data-driven approaches, classification algorithms, natural language processing (NLP), hybrid recommender systems, and sentiment analysis in improving treatment efficacy. This survey further analyzes the comparative performance, identifies research gaps, and proposes methodologies to enhance accuracy, interpretability, and personalization in ML-based healthcare systems.

1. INTRODUCTION

In recent years, the healthcare industry has witnessed a paradigm shift driven by the integration of Artificial Intelligence (AI) and Machine Learning (ML) technologies. These technologies have enabled systems to predict diseases, personalize drug recommendations, and enhance the efficiency and accuracy of healthcare services. The increasing complexity of patient data, including electronic health records (EHRs), genomic sequences, and user-generated content such as reviews and ratings, necessitates advanced analytical models for extracting meaningful insights.

Traditional healthcare systems often rely on heuristic rules and manual diagnostics, which may not account for hidden patterns in the data. In contrast, machine learning models are capable of identifying complex correlations and generating predictive insights from high-dimensional data. Predictive analytics and recommendation systems have already demonstrated value in applications ranging from chronic disease management to pharmacovigilance. Moreover, with the emergence of Natural Language Processing (NLP), unstructured text data from clinical notes and patient feedback can now be effectively utilized. This combination of structured and unstructured data has led to significant improvements in predictive modeling and personalized medicine. The use of ensemble methods and hybrid systems is particularly noteworthy, as they allow for a combination of different algorithms to produce more reliable results.

Despite these advancements, several challenges persist, including data sparsity, bias in training data, lack of model interpretability, and concerns over patient privacy. These challenges highlight the importance of continuous innovation in algorithm development and the need for collaborative frameworks involving clinicians, data scientists, and policymakers.

Healthcare is undergoing a significant transformation through the adoption of machine learning (ML) and artificial intelligence (AI). With massive digital health data available from hospital information systems, electronic health records (EHRs), and patient feedback, intelligent systems can now predict diseases, analyze patient symptoms, and recommend personalized medications. Disease prediction systems (DPS) and drug recommendation engines are emerging technologies that assist in reducing diagnostic errors and enhancing treatment outcomes. This literature review aims to investigate and analyze contemporary techniques used in developing these intelligent systems, focusing on their methodologies, effectiveness, datasets, and application domains.

2. LITERATURE REVIEW

This section presents a detailed review of works by various authors who contributed to the development of intelligent disease prediction and drug recommendation systems using machine learning. Each subsection highlights the key contributions, datasets, algorithms, and outcomes.

Nayak et al. (2023): proposed a robust disease prediction and drug recommendation prototype using four machine learning models, namely Multinomial Naive Bayes, Decision Tree, Extra Tree, and SVM. The model incorporated NLP techniques and sentiment analysis to improve drug recommendations. [1]

The current study examines how the Internet of Things and artificial intelligence in the Industry 4.0 framework enable fault identification and categorization in manufacturing. Three artificial intelligence algorithms—

Naive Bayes, Extreme Gradient Boosting, and k-Nearest Neighbors—are compared in this IoT-based study. Therefore, to improve defect detection and classification in manufacturing, end users must integrate sophisticated machine learning algorithms with understandable explanations. Better production procedures and more innovation in Industry 4.0 manufacturing will be made possible as a result.

Rustam et al. (2022): developed a real-time disease diagnostic system reaching 99.9% accuracy using supervised learning models. [10]
The paper suggests a Convolutional Neural Network-based automated deep learning-based classification model that exhibits a quick COVID-19 detection rate. 10,192 healthy chest X-ray pictures and 3616 COVID-19 chest X-ray images make up the training dataset. These images were then enhanced. Eleven pre-existing CNN models were used to identify COVID-19 symptoms using the dataset. MobileNetV2 shown enough potential to warrant additional development.

Bhimavarapu et al. (2022): implemented a drug recommender using a stacked artificial neural network to reduce adverse effects by analyzing health history, reporting 97.5% accuracy. [5]
In order to solve the pressing issues of data integrity and privacy in the contemporary healthcare environment, the study presents a novel method to healthcare data security. By combining attribute-based access control (ABAC), blockchain technology, and AWS S3 services, the suggested solution provides a strong foundation for protecting private medical data. Only authorized entities may access and change healthcare data thanks to the solution's dynamic and precise access control made possible by the adoption of ABAC. Additionally, by offering an unchangeable and impenetrable storage method, the use of a blockchain-based XML ledger on AWS S3 services improves data security. In addition to addressing the privacy issues raised by the digitization of healthcare, our all-inclusive solution makes it easier for authorized parties to share data securely. Through the integration of blockchain technology, ABAC, and AWS S3 services, the suggested architecture provides a scalable and effective platform for safely handling healthcare data. In an increasingly linked digital world, it promises to protect patient privacy and preserve the quality and dependability of medical data, marking a substantial development in healthcare information security.

Gupta et al. (2021): used Decision Tree, Random Forest, and Naive Bayes classifiers to predict diseases from symptoms and associate them with the correct medications. They reported an accuracy of over 98% with Naive Bayes. [2]
The design and development of a novel anomaly-based intrusion detection model for Internet of Things networks is presented in this research. First, a multiclass classification model is developed using a convolutional neural network model. Convolutional neural networks are then used to implement the suggested model in 1D, 2D, and 3D. The BoT-IoT, IoT Network Intrusion, MQTT-IoT-IDS2020, and IoT-23 intrusion detection datasets are used to test the suggested convolutional neural network model. Using a convolutional neural network multiclass pre-trained model, transfer learning is employed to accomplish binary and multiclass classification. When compared to current deep learning implementations, our suggested binary and multiclass classification models have demonstrated good accuracy, precision, recall, and F1 score.

Tran et al. (2021): provided a meta-review of healthcare recommender systems, classifying them based on recommendation type and algorithms used. [15]
An overview of FL techniques is given in this study, with an emphasis on edge devices with constrained computing capabilities. Additionally, prominent FL frameworks that facilitate client-server communication are presented in this study. Numerous subjects are discussed in this context, including literary contributions and trends. This covers resource management, privacy and security, practical application possibilities, and fundamental system architecture models and designs. There is discussion of issues including hardware heterogeneity, communication overload, and device resource limitations that are associated with the computing demands of edge devices.

Olsen et al. (2020): reviewed heart failure classification using decision trees, SVMs, and deep learning, validating ML's utility in diagnostics. [8]
A realistic yet artificial predictive maintenance dataset is presented and made available for the community's and this paper's usage. An explainable model and an explanatory interface are provided, trained using the dataset, and their explanatory performance tested and contrasted.

Chen et al. (2018): introduced the DDTRS system, leveraging cloud computing and big data mining for diagnosis and drug recommendations using DPCA and Apriori algorithms. [6]
Secure forest, agricultural, and tourism sectors can lead to economic growth and human protection via the application of an effective and economical weather forecasting technique. The Weather4cast 2021 challenge

dataset from IEEE Big Data IARAI served as the basis for this work. This paper's objective is to examine the computing cost of forecasting future weather using a neural network model based on CNN-LSTM. The network predicts future weather pictures using an encoder-decoder architecture.

Bao and Jiang (2016): developed a medicine recommender system using SVM, ID3, and BP neural networks, selecting SVM due to its high accuracy (95%) for final deployment. [3]
The secret to making the most of highways' carrying capacity and enhancing the travel experience is accurate traffic flow forecasting. A novel hybrid model for short-term traffic flow prediction based on spatiotemporal deep learning with consideration for related factor selection is provided in order to overcome the unpredictability and volatility of traffic flow. The Pearson Product-Moment Correlation Coefficient (PPMCC) is used to identify traffic flow with high spatial relevance in this model. Random Forest (RF) is then used to screen for associated factors affecting traffic flow. Lastly, the output of the two aforementioned steps and the historical traffic flow data are used as input, both the Bidirectional Gated Recurrent Unit (BiGRU) and Convolutional Neural Network (CNN) are utilized to forecast traffic flow by detecting the spatiotemporal features of traffic flow and the hidden connections between different elements.

Zhang et al. (2015): suggested a hybrid recommendation system combining ANN and Case-Based Reasoning (CBR) for clinical prescribing. [4]
The big data analytics and related smart grid applications are introduced in this study. Before demonstrating the rationale and possible benefits of integrating sophisticated data analytics in smart grids, the definitions of big data, smart grids, and massive data collecting are first covered. Additionally covered are the fundamental ideas and methods of standard data analytics for generic issues. The primary focus of this study is on advanced applications of various data analytics in smart grids. In the big data era, several advantages may be added to the current power system and enhanced customer service and societal welfare by handling vast amounts of data from the electrical network, weather information system, geographic information system, etc. However, a number of challenges, including awareness, methodologies, and synergies, must be resolved in order to develop the uses of big data analytics in actual smart grids.

Feldman et al. (2015): discussed the integration of disease prediction systems in personalized healthcare and emphasized scalability. [12]
Numerous unstructured and semi-structured material sources, such as emails, social media, videos, customer reviews, help requests, and questions, are available and might yield important insights. In order for corporate processes to function efficiently and proactively, NLP tools and techniques aid in the analysis and comprehension of all such data. Using automatic summarization, speaker diarization, and entity extraction, NLP can also examine the patterns that emerge in text/audio entries in big data by closely examining the linguistic and semantic statistics to identify important entities and relationships in relation to what the customers are attempting to convey in their feedback. NLP is capable of comprehending and extrapolating meaning from both spoken and written communication.

Bhat and Aishwarya (2013): presented a hybrid recommender using collaborative and content-based filtering to recommend newly marketed drugs. [11]
Sensor nodes positioned to gather data about the surrounding environment make up Wireless Sensor Networks (WSNs). WSNs are extremely susceptible to security attacks at many levels because of their dispersed nature, multihop data forwarding, and open wireless medium. Security attack detection and prevention may be greatly aided by intrusion detection systems, or IDSs. Current intrusion detection systems and certain unresolved WSN security research issues are presented in this study.

Austin et al. (2013): compared flexible tree-based models with traditional classifiers for heart failure subtype classification, showing improved accuracy. [13]
With the potential to use enormous volumes of patient data for disease prevention and prediction, treatment plan optimization, and service improvement, predictive analytics has become a game-changing tool in the healthcare industry. Predictive analytics is at the forefront of innovation in the healthcare sector, with the potential to improve patient outcomes, save costs, and allocate resources more effectively. This study examines the state of predictive analytics in healthcare today and the exciting potential it has to revolutionize healthcare administration and delivery.

AbuKhousa et al. (2012): analyzed various predictive data mining models for heart disease, highlighting poor generalization from small datasets. [14]
High threats to data security and privacy result from the convergence and integration of several services with disparate ownership and capability, which are unavoidable in e-health care systems. Numerous suggestions have been made to address some of these

issues either separately or in combination with other methods. In this paper we define different scenarios for the integration of the e-health systems with the cloud computing systems. Along with outlining the standards for the suggested fixes for the security and privacy issues raised, we also specify the security and privacy criteria for these circumstances.

Hussein et al. (2012): proposed a clinical disease diagnosis system using RF, J48, and REP classifiers, achieving 99.7% accuracy with RF. [9]
Through the internet, cloud computing has a tremendous potential to provide customers more flexible and cost-effective on-demand services. The main barrier to this new idealized picture of computing capabilities is security, even as we move toward the idea of on-demand service, resource pooling, and moving everything on the distributive environment. It addresses a few private and public cloud authorities as well as associated security issues. It also proposes a three-tier security architecture and covers the prerequisites for improved security management.

Kononenko et al. (1997): demonstrated that decision trees and neural networks can significantly improve diagnostic precision and reduce costs. [7]
Effective illness diagnosis is a significant unmet need on a global scale. Developing an early diagnosis tool and a successful treatment plan is extremely difficult due to the complexity of the many disease processes and underlying symptoms of the patient group. A branch of artificial intelligence (AI) called machine learning (ML) helps patients, doctors, and researchers address some of these problems. The most current developments and methods in machine-learning-based disease diagnosis (MLBDD) are then summed up in the review, taking into account the following elements: algorithm, illness kinds, data type, application, and evaluation metrics

3. COMPARATIVE ANALYSIS

The comparative analysis of intelligent disease prediction and drug recommendation systems reveals considerable diversity in methodologies, datasets, evaluation metrics, and domains of application. Researchers have experimented with a variety of machine learning models to improve diagnostic precision, from conventional classifiers like Decision Trees and Naive Bayes to sophisticated approaches like Neural Networks and Support Vector Machines (SVMs). This section highlights the core differences and similarities across the literature surveyed.

Machine Learning Algorithms: A wide range of classification models are used to predict diseases based on symptoms. Nayak et al. [1] utilized four classifiers—Multinomial Naive Bayes, Decision Tree, Extra Tree, and SVM—whereas Gupta et al. [2] focused on Naive Bayes, Random Forest, and Decision Trees. Bhimavarapu et al. [5] adopted a stacked neural network for more complex patient profiling. The preference for ensemble and hybrid models indicates an increasing trend toward combining the strengths of individual models for better accuracy and interpretability.

Recommendation Mechanisms: Drug recommendation strategies differ across the studies. Bao and Jiang [3] relied on data mining-based filtering using SVMs, while Rustam et al. [10] incorporated precautionary advice with diagnostic outputs using supervised learning. Some models, such as those by Zhang et al. [4] and Tran et al. [15], integrated collaborative filtering and content-based strategies, providing a more personalized approach. NLP-based models are also popular; Nayak et al. [1] and Alsaif et al. [4] utilized sentiment analysis to map user reviews to medication efficacy.

Datasets: A consistent challenge in all research is access to quality datasets. Public datasets such as those from the UCI Repository and New York-Presbyterian Hospital are frequently used, but limitations in data size and noise persist. Nayak et al. [1] used three different datasets to enhance disease-drug mapping: symptom records, drug reviews, and side effect databases. Others like Feldman et al. [12] emphasized the importance of integrating multiple data streams to improve prediction models.

Accuracy and Evaluation Metrics: Accuracy remains a major focus of evaluation. Gupta et al. [2] reported a maximum accuracy of 98% using Naive Bayes, while Bhimavarapu et al. [5] achieved 97.5% with ANN. Nayak et al. [1] achieved above 88% with all four classifiers used. However, Rustam et al. [10] surpassed others by obtaining 99.9% accuracy using supervised learning. Despite high accuracies, very few papers emphasized metrics like precision, recall, or F1-score which are more indicative of real-world diagnostic reliability.

Hybrid Systems: Several studies proposed hybrid systems for improved performance. Hussein et al. [9] combined multiple classifiers including Random Forest, which yielded the highest accuracy at 99.7%. Zhang et al. [21] applied hybrid matrix factorization along with sentiment analysis to predict user preferences in healthcare. These hybrid systems offer the benefit of combining structured symptom data with unstructured textual reviews, resulting in enhanced personalization.

Technological Integration: Modern systems increasingly incorporate NLP, big data analytics, and real-time cloud computing. Chen et al. [6] deployed a cloud-based DDTRS that uses Apache Spark for low-latency performance. Nayak et al. [1] implemented NLP with the VADER tool and neural network classifiers. As evident from these efforts, scalability, responsiveness, and automation are becoming critical aspects.

Strengths and Limitations: Each approach has its benefits and trade-offs. Naive Bayes offers simplicity and high speed but lacks sophistication for contextual understanding. Neural networks provide better learning but are opaque and computationally expensive. Hybrid models are promising but often depend on heavy data preprocessing and fine-tuning. Moreover, limitations in generalization due to dataset bias and lack of clinical validation remain major concerns.

Emerging Trends: The trend is shifting toward explainable AI (XAI), privacy-preserving models, and integration with wearable health tech. Additionally, the importance of model interpretability is being emphasized in clinical settings, where doctors need transparent systems for decision support.

In summary, while many models demonstrate impressive accuracy, the most effective systems are those that integrate multiple models and datasets, incorporate real-world feedback through sentiment analysis, and leverage scalable infrastructures like cloud computing. Each system contributes uniquely to the growing body of work in intelligent healthcare, and their comparison highlights the evolving complexity and multidisciplinary nature of this domain.
In addition to the works already discussed, several other studies have advanced the state-of-the-art in this domain.

Morales et al. (2022) [16] developed a drug recommendation system for diabetes patients using a combination of collaborative filtering and clustering techniques. They reported encouraging accuracy using principal component analysis (PCA) and user-based collaborative filtering. Their work emphasizes the importance of dimensionality reduction when dealing with large healthcare datasets.
Zhang et al. (2017) [17] proposed iDoctor, a professionalized medical recommendation system that uses hybrid matrix factorization in conjunction with sentiment analysis. The system successfully filtered emotional noise in reviews and provided accurate doctor recommendations. This study demonstrates how sentiment extraction can be fine-tuned for medical applications.
Kuanr et al. (2021) [18] examined a health recommender system focused on predicting cervical cancer prognosis using multiple classifiers including Logistic Regression, SVC, Decision Tree, and XGBoost. Their findings showed the superior performance of Gradient Boosting Machine (GBM), validating the effectiveness of boosting algorithms in healthcare prediction.
Han et al. (2018) [19] introduced a hybrid recommender system for patient-doctor matchmaking using collaborative and content-based filtering. The model achieved 80% accuracy and outperformed conventional heuristic baselines, indicating that hybrid approaches can improve decision-making in primary care environments.
Mudaliar et al. (2019) [20] presented a virtual doctor application that uses machine learning to predict diseases and recommend drugs based on symptoms. Their system integrates disease diagnosis with medicine prescription and serves as a proof-of-concept for mobile-based clinical decision support systems.
These extended studies illustrate the dynamic nature of intelligent systems in medicine. They incorporate diverse methods—ranging from collaborative filtering to boosting and sentiment analysis—to tackle the multifaceted challenges of diagnosis and treatment recommendation.

4. RESEARCH GAPS AND METHODOLOGY

Despite notable progress in machine learning-based disease prediction and drug recommendation systems, several critical research gaps persist. These limitations present opportunities for future exploration and refinement.

• **Data Limitations**: A significant number of studies depend on publicly available datasets such as those from UCI or hospital-specific repositories. These datasets often suffer from class imbalance, missing values, and limited diversity in demographic and clinical variables. Generalizability of models trained on such datasets is a common concern.

• **Model Interpretability**: Many advanced machine learning models, particularly deep neural networks, are black boxes. Their lack of interpretability hinders clinical adoption, as healthcare professionals require transparent and explainable systems to make informed decisions.

• **Sentiment Noise in NLP**: Sentiment analysis models applied to drug reviews often suffer from misclassification due to sarcasm, cultural bias, or ambiguous language. This can affect the reliability of recommendation engines, especially in emotionally charged healthcare contexts.

• **Lack of Real-Time Adaptability**: Most models are static and do not adapt in real time to evolving patient data. Real-world applications require dynamic systems that continuously learn and update predictions and recommendations.

• **Integration with Clinical Workflows**: Few studies address how ML-based systems integrate with existing hospital information systems (HIS) or electronic health records (EHRs). Practical implementation remains a major hurdle.

• **Ethical and Legal Concerns**: Issues such as data privacy, informed consent, and model bias are insufficiently addressed in many studies. Ensuring ethical compliance and robust validation is crucial before real-world deployment.

METHODOLOGY

To address these gaps, the proposed research framework focuses on building a robust and interpretable system for disease prediction and drug recommendation using the following methodology:

1. **Data Collection and Preprocessing**:
- Utilize multiple open-source medical datasets, including symptom-disease associations, drug reviews, and adverse effect reports.
- Perform data cleaning, normalization, and feature engineering.

2. **Model Development**:
- Develop four machine learning models: Multinomial Naive Bayes, Decision Tree Classifier, Extra Tree Classifier, and SVM.
- Train models using one-hot encoded symptom vectors for disease prediction.

3. **Sentiment Analysis**:
- Use NLP tools like VADER and TF-IDF-based neural network classifiers to evaluate sentiment polarity in drug reviews.
- Incorporate review ratings and helpfulness counts to compute weighted scores.

4. **Drug Recommendation**:
- Combine sentiment analysis outcomes with disease predictions.
- Rank drugs using weighted average and probabilistic scores to ensure the most effective medications are recommended.

5. **Evaluation**:
- Evaluate models based on accuracy, precision, recall, and F1-score.
- Use cross-validation and real-world validation to assess performance.

6. **Interpretability and Visualization**:
- Implement model explainability techniques such as LIME or SHAP to provide insights into model decisions.

7. **Deployment Consideration**:
- Design a scalable, API-based architecture to integrate with clinical platforms for real-time use.
This methodology aims to bridge the gap between theoretical model performance and practical, interpretable, and ethical deployment in healthcare environments.

5. CONCLUSION

This literature survey examined over twenty significant contributions in the domain of machine learning-based disease prediction and drug recommendation. From traditional classification models to advanced hybrid systems integrating NLP and sentiment analysis, the field has seen tremendous innovation. While the reported results are encouraging, the challenges of data quality, interpretability, integration, and ethical compliance continue to impede real-world implementation. This paper highlights the comparative performance of various models, presents critical research gaps, and outlines a robust methodology aimed at improving model accuracy, reliability, and clinical relevance.

By advancing models that are explainable, adaptable, and aligned with ethical and operational requirements, the proposed system aspires to support healthcare providers in delivering personalized, data-driven care. Future research can further explore deep learning, federated learning for privacy-preserving analytics, and multi-modal data fusion to enhance predictive power and scalability.

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