DRUGS PREPOSTEROUS PHARMACOVIGILANCE CLASSIFICATION USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TECHNIQUES

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Abstract: Artificial intelligence (AI) technologies have recently played an essential role in the health sector. One of the most important uses of these technologies is determining drug side effects. The purpose of side-effect studies is to increase the safety and effectiveness of drugs. Early detection of side effects can provide patients with a better treatment option and a better roadmap for healthcare providers. Therefore, side-effect studies are an essential tool for the healthcare industry. Drug side effects can be a serious problem for patients, and in some cases, even life-saving drugs can become unusable due to their side effects. Therefore, early detection and prevention of side effects are vital. Artificial intelligence and explainable artificial intelligence (XAI) technologies provide faster, more accurate, transparent, and explainable results compared to traditional methods of determining the side effects of drugs. These technologies can detect the side effects of drugs by analyzing large amounts of data and can also be used in developing new drugs. With the use of these technologies, the determination of drug side effects can be performed more quickly and effectively. These technologies also eliminate the limitations encountered in traditional methods used to detect the side effects of drugs.

Keywords: Pharmacovigilance, Artificial Intelligence, Machine Learning, Supervised Learning Algorithms

I. INTRODUCTION

Artificial Intelligence (AI) is among the technologies that can be used to help detect the side effects of drugs more quickly and accurately [1]. Pharmacovigilance is the process of monitoring, evaluating, and reporting the side effects of drugs. After the drugs are put on the market, side effects reported by patients and healthcare professionals are collected through the pharmacovigilance system, and the possible risks of these side effects are evaluated. This process plays a vital role in the safety of drugs and helps protect public health [1]. AI technologies enable rapid analysis of large data sets. This can help analyze data collected during the pharmacovigilance process faster and more accurately. AI technologies have the potential to

discover new relationships by analyzing data to detect side effects. This can help to understand better and report the side effects of drugs. It can also assist in automatically processing data in the pharmacovigilance process. This saves time for pharmacovigilance professionals and can speed up the process of collecting more data for detection of side effects [2]. As a result, in this study, it is detailed that AI and explainability can help detect side effects more quickly and accurately and play an essential role in the safety of drugs. Ensuring patient safety is an indispensable principle of health services. Since every stage of healthcare

has the potential to trigger an error. Some problems may arise in healthcare services' delivery, products, or procedures. The most common problem with drugs is the occurrence of side effects [3]. The therapeutic effects of drugs often bring side effects. The therapeutic range of a drug can be defined

as the dosage range or serum concentration in which it is expected to achieve the desired therapeutic effect. The therapeutic range does not mean the drug cannot provide benefits at concentrations below the minimum threshold or produce adverse effects when kept within the range [4]. Side effect: It is defined by the World Health Organization (WHO) as "an unintended harmful response to a drug used at normal doses for the prophylaxis, diagnosis, treatment of a disease or for modifying physiological function". Side effects can range from mild dizziness to death in the most severe form. There are two types of side

effects:

1. Type A reactions are dose-dependent reactions that can be predicted based on the pharmacology of the drug.
2. Type B reactions are idiosyncratic and unpredictable based on pharmacology [5]. Factors that predispose to the side effects of drugs; include dose, the chemical structure of the drug, patient-related factors, pregnancy, polypharmacy, and drug interactions. Different factors influence the development of side effects to varying degrees. These factors should be considered to prevent or reduce undesirable drug effects. In addition, information technology should be part of the decision-making process for drug therapy. This way, healthcare professionals stay up-to-date on drug dosing, drug interactions, side effects, and other important information needed to use the drug optimally [6].

Dosage and time of administration
Drug dosing affects the development of side effects in many ways. The side effects of some drugs develop in a dose-dependent manner [5]. The drug's administration time may also cause the effect and side effects of the drug to change. Some medications must be given in the morning, some in the evening, and some before bed [6].

Chemical structure of the drug

The dynamics governing the drug's reaction largely depend on the structural arrangement of functional groups. The drug's chemical structure determines its physicochemical properties, absorption, distribution, metabolism, excretion and toxicity (ADME/TOX) properties. Finally, the pharmacological activity of the drug molecule and the side effects it may cause largely depends on the drug's chemical structure. Therefore, it is crucial to investigate the impact of functional groups on side effects to synthesize drugs with few side effects [6- 8].

Patient-related factors
   Age
All drugs can cause side effects, but not all patients develop

the same level and type of side effects. The elderly and pediatric patients are particularly susceptible to adverse impacts because the absorption and metabolism of drugs are more variable and less predictable in both groups.
Gender
   Anatomical and physiological differences depending on gender may cause the effect of drugs to change. Women have lower body weight, more body fat, different gastric motility, and a lower glomerular filtration rate than men. These differences can change the pharmacokinetics and pharmacodynamics of drugs.

Pregnancy
   Physiological changes in the body during pregnancy affect the pharmacokinetic and pharmacodynamic properties of the drug. The change in the distribution and elimination properties of the drug causes the side effect to change as well. Creatinine clearance Creatinine clearance reflects the function of the kidneys, which are responsible for the excretion of

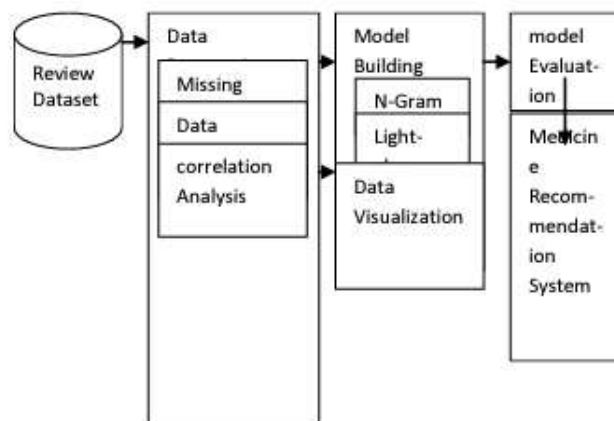
Fig 1: System Architecture

   many drugs. Any change in kidney profile may increase drug toxicity or reduce the therapeutic effect.
Drug-related factors
Polypharmacy
   Taking more than one drug simultaneously increases the risk of side effects by causing drug interactions. The severity of the side effect increases disproportionately as the number of drugs taken increases [8].. medical practice, especially regarding approving new drugs or questioning the possibility of a drug being withdrawn from the market [9]. It guides pharmacological treatment and effectively decides which drug should be given to a patient. The fact that there are many drugs on the market and the misuse of drugs that can cause serious side effects has made the issue of drug safety one of the most critical health problems of the age. The drug safety problem referred to as the 'thalidomide disaster' in the

literature is related to the use of this contraindicated drug for morning sickness by many pregnant women in Europe in the late 1950s. The fact that the side effects it may cause have not been adequately investigated has led to the congenital disease known as phocomelia [10]. Drug side effects are an essential parameter in evaluating the safety of drugs. The most critical factor in the emergence of drug safety problems; The reason for this is that the understanding of possible side effects is insufficient due to the longterm and complex clinical studies. For this reason, drugs may enter the market without all their side effects being detected [11]. Pharmacovigilance studies include systematic monitoring of adverse drug reactions and determination of the safety and efficacy of drugs. The WHO defines pharmacovigilance as "the science and activities concerned with the detection, assessment, understanding and prevention of adverse effects or other drug-related problems" and plays a crucial role in ensuring that patients take safe drugs [12]. It enables monitoring the drug's effect in various patient types with comorbid diseases. The potential user population of a drug is very different from the population studied during clinical trials prior to the drug's approval. For example, significantly few clinical trials will involve very elderly patients or patients with comorbidities or breastfeeding women [13]. All drugs have side effects, but their efficacy and severity range from mild (such as mild itching or mild headache) to severe (severe rash, damage to vital organs, particularly the liver and kidneys, and even death). Most of the side effects are predictable. However, the side effects of some drugs and the effects that may occur as a result of their use in special populations cannot be predicted [9]. Today, many studies are carried out to determine the side effects of drugs. Identification of drug side effects is considered an important step in drug design. Because these studies not only save time but also reduce the cost of drug development [14]. Side effect studies on a drug can be divided into the design phase of the drug, the clinical research phase before it is put on the market, and the studies after it is made available [13-15]. Studies of identifying drug side effects with traditional approaches are divided into ligand-based and docking approaches. However, the quantitative structure-activity relationship performs poorly in predicting candidate ligand binding using machine learning methods when reducing the number of ligands for target proteins. The docking approach cannot be applied to proteins with unknown 3D structures [14, 15]. The clinical research phase of drug development studies investigates drug safety, effects and side effects clinically. At this stage, drugs are administered to people with the disease intended to be treated, and side effects are tried to be detected. However, these studies are not comprehensive enough to identify all the side effects that the drug may cause. Therefore, studies to determine side effects continue after

the drug is released on the market [15]. Postmarketing surveillance of drugs involves identifying and collecting drug-related information after the drug has been approved for use in a population. It is a method of systematically monitoring the safety and efficacy of new drugs in the real world using a variety of patient types with many different comorbid diseases [13]. No single method is used in the surveillance of adverse drug reactions. Individual case reports include reports submitted to national regulatory authorities and anecdotal reports in medical journals. Cohort-event monitoring allows the quantification of adverse event rates. Cohort sizes typically range from a few thousand to tens of thousands of patients. Allows estimation and comparison of incidence rates among medicinal products. Analysis of longitudinal patient records can detect a wide variety of temporal patterns between medical diagnoses and drug prescriptions [16].

Traditionally, side effects of drugs are monitored by humans during clinical trials and postmarketing monitoring processes. However, these methods may be insufficient in detecting and reporting side effects. Therefore, using AI technologies can help detect the side effects of drugs more accurately [1, 17-19]. AI can detect and report side effects based on large amounts of data [20]. This data may include patients' health records, drug manufacturers' reports, results of clinical trials, side effect reports, and other health records. By analyzing this data, AI can identify possible causes and mechanisms of drug side effects [17, 21]. However, there are also some difficulties with the use of AI technologies. For example, data collection and analysis can take a lot of time, and it is important to use the right data to get accurate results. It should also be noted that AI technologies may not accurately detect side effects. Therefore, using AI to detect the side effects of drugs may give a more effective result when combined with other methods [1, 22, 23]. Several studies exist on using AI technologies to detect the side effects of drugs [24]. Data mining studies: These studies use artificial intelligence technologies to explore relationships between drug use and adverse effects in large existing datasets [25-27]. Natural language processing studies (NLP): These studies use artificial intelligence technologies to analyze natural language data such as reviews, health records, and other documents written by drug users [28, 29]. AI-assisted clinical trials: These studies use artificial intelligence technologies in clinical trials to detect the side effects of drugs. These studies can increase the efficiency of experiments and speed up the detection of side effects [30]. Machine learning studies use machine learning techniques to learn complex relationships between drug use and side effects [31]. Classification studies use artificial intelligence technologies to classify drug use and side effects associations. These classifications can help accurately report drug side effects [32]. There are many review articles on the

use of artificial intelligence in pharmacovigilance. Only a few of these articles have focused on explainability. The difference in this study is that it focuses on both AI and XAI and their use in the field of pharmacovigilance.

II. LITERATURE SURVEY

Recommender frameworks point to supply clients with personalized stock and repair to alter the expanding online information over-burden drawback. Various recommender framework methods are anticipated since the mid1990s,and numerous shapes of recommender framework code were created as of late for a spread of applications. Most of the recommender advances unit of measurement connected to the e-government area[2], e-business area[3], e-commerce/e-shopping area[4], e-learning area[5] and etourism area[6] etc. The medication space incorporates uncommon recommender innovations, and this paper centers on arranging of the medication recommender framework and mining data from therapeutic case knowledge. Through on-line social organizing, the communication is monstrously progressed and totally distinctive intrigued of information is advertised on net essentially at the open pace. The total diverse information must share to chronicle highlights of potential edges and availability of utilities bits of knowledge, things, people practices and items, etc. [7]. One in all the vital areas is that the therapeutic and well being sciences is to think approximately social angles through on-line dialogs, blogs, audits, and on-line overviews, etc. [9]. The health-related substance shared through on-line feedbacks or surveys contains covered up assumption [10] designs that emerges through totally distinctive sources from medical world which offer benefits to the pharmaceutical industry[8]. Amid this, the on-line component is fantastically standard of late for online looking, diverse stock through distinctive websites like on-line buying of drugs at entryway step. Numerous websites and blogs offers clients to rate their stock with their fulfillment and quality of stock, logistics, administrations and criticism etc. , which the clients examines for a particular medicine or on quality of administrations

III. REQUIREMENT OF EXPLANATION ON PHARMACOVIGILANCE

Explainable artificial intelligence (XAI) can be used in the field of pharmacovigilance, making the monitoring and reporting of drug side effects more efficacious [34-37]. By processing pharmacovigilance data, XAI can predict potential side effects and risks. These systems can analyze large amounts of data to detect possible side effects of drugs. In addition, XAI systems can more accurately predict side effects by considering other factors related to a drug's interactions or use. This technology can assist in developing medicinal products and vital research to ensure patients' safety and make the pharmacovigilance process more accurate, faster and more efficient. XAI is an approach that aims to provide transparency and an explanation of how artificial intelligence, its algorithms, or other automated decision-making systems work. This is extremely important for people to understand and increase the reliability of decisions and forecasts [38]. SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) methods can be used in pharmacovigilance assessments of drug safety and to understand the causes of side effects. SHAP is used to identify the importance of features that contribute to the operation of machine learning models. In pharmacovigilance, the SHAP method can analyze drug efficacy and side effects on several characteristics (age, gender, disease status, drug dosage, etc.). LIME is a method that reduces the complexity of machine learning models. In pharmacovigilance studies, the LIME method can reveal causes related to a particular side effect of a drug. Specifically, the LIME can identify why a drug causes different side effects for a specific patient population or disease state. The SHAP and LIME methods are valuable tools for obtaining information about drug efficacy and side effects in pharmacovigilance. These methods can provide more efficient and informative results than traditional drug safety assessment methods [17]. Machine learning is a hot topic in research and industry, with new methodologies developed all the time. The speed and complexity of the field makes keeping up with new techniques difficult even for experts and potentially overwhelming for faster analysis.

Research in AI and pharmacovigilance shows that it can help detect the side effects of drugs more quickly and accurately. These technologies are highly effective in analyzing large datasets so that possible risks of side effects can be detected at an earlier stage. In addition, AI technologies offer higher accuracy in analyzing side effects, helping to understand side effects better. Studies in the field of pharmacovigilance have demonstrated the potential advantages of these technologies. However, there are also some disadvantages associated with using AI. These include issues such as data security and privacy, the accuracy of algorithms, and whether they can replace human expertise in recognizing side effects. In addition, the use of AI in the field of pharmacovigilance also opens up ethical issues in the pharmaceutical industry. For example, there is a concern that pharmaceutical companies might use these technologies to hide the side effects of drugs. Therefore, it is necessary to establish clear and transparent regulations on utilizing AI technologies in pharmacovigilance. Consequently, the use of AI in the field of pharmacovigilance may play an essential role in the safety of drugs. However, the disadvantages of its use, such as ethical and safety issues, should also be considered, and steps should be taken to resolve these issues.

IV. PROPOSED SYSTEM

In this segment, the characteristics of the recommender framework are reaching to be specified, additionally the detail of our drugs recommender framework system are aiming to be presented. Recommender framework has gotten to be a profitable investigation field as the advancement of counterfeit brilliantly advances. Not at all like most current recommender frameworks that specialize in e-business, book and pictorial suggestion, our framework points at giving a virtual fully fledged specialist for unpracticed amateurs and patients in abuse right pharmaceutical. Since high accuracy and strength is vital for such an online pharmaceutical recommender framework, in this way we tend to evaluate a few information preparing approaches to induce an genuine trade-off among the precision, productivity and

quantifiability. In this proposed System, the framework mainly consists of five modules, as shown in figure 1, which are (i) Database module (ii)Data preparation module (iii)Recommendation model module (iv)Model evaluation model and (v)Data visualization module. Through this process set the topic, preprocess the data to fit the objective, and create various variables to fit model. At the model part, emotion analysis using word dictionary, applying deep learning, etc. were used and then accuracy of both the algorithms is evaluated.

Existing System

The study presents GalenOWL, a semantic-empowered online framework, to help specialists discover details on the medications. The paper depicts a framework that suggests drugs for a patient based on the patient's infection, sensitivities, and drug interactions. For empowering GalenOWL, clinical data and terminology first converted to ontological terms utilizing worldwide standards, such as ICD-10 and UNII, and then correctly combined with the clinical information. Leilei Sun examined large scale treatment records to locate the best treatment prescription for patients. The idea was to use an efficient semantic clustering algorithm estimating the similarities between treatment records. Likewise, the author created a framework to assess the adequacy of the suggested treatment. This structure can prescribe the best treatment regimens to new patients as per their demographic locations and medical complications. An Electronic Medical Record (EMR) of patients gathered from numerous clinics for testing.

Disadvantages of Existing System

- In the existing work, the system did not implement an exact sentiment analysis for large data sets.
- This system is less performance due to lack Data Classification and Data Fragmentation technique.

Proposed System

The aim of this study was to review the literature on the use of XAI in PV by identifying publications related to ML/AI and drugs and the rationale for the reported findings. From the perspective of AI and XAI usage, these studies were analyzed, and the findings were summarized, in which the use of XAI in the field of PV is referred to as ''PV XAI''. The main contributions are highlighted and discussed below:
- This study is clearly an early attempt to review XAI research in PV. Unlike other fields, we found that XAI research in PV is at an early stage of development, limited to

a few articles and some methodologies.
- Nevertheless, we have identified the positive potential of PV XAI for drug therapy, ADRs, poly pharmacy and drug repurposing.
- While safety issues in real-world healthcare settings may limit the growth of the field, we expect PV XAI research to expand as it has in other areas, and we
encourage collaboration and ongoing research discussions with experts in the field.

Advantages of Proposed System

- We propose Deep neural networks (DNNs) are the foundation of modern AI models.

- 2) The proposed system implemented Tree-based algorithms in which conceptually simple but powerful ML methods that are effective on small and large datasets to solve linear and nonlinear modeling problems..

Application Modules

In this segment, the characteristics of the recommender framework are reaching to be specified, additionally the detail of our drugs recommender framework system are aiming to be presented. Recommender framework has gotten to be a profitable investigation field as the advancement of counterfeit brilliantly advances. Not at all like most current recommender frameworks that specialize in e-business, book and pictorial suggestion, our framework points at giving a virtual fully fledged specialist for unpracticed amateurs and patients in abuse right pharmaceutical. Since high accuracy and strength is vital for such an online pharmaceutical recommender framework, in this way we tend to evaluate a few information preparing approaches to induce an genuine trade-off among the precision, productivity and quantifiability. In this proposed System, the framework mainly consists of five modules

- Database module

- Data preparation module

- Data Exploration

- Data Preprocessing

- Data visualization module.

Through this process set the topic, preprocess the data to fit the objective, and create various variables to fit model. At the model part, emotion analysis using word dictionary, applying deep learning, etc. were used and then accuracy of both the algorithms is evaluated.

Database System Module:

It contains a drug review dataset with attributes like unique Id, drug name, condition(disease of patient), date , useful count, reviews and ratings given by the patients on the drugs.

Data Preparation Module:

It comprises of information investigation and information preprocessing. The real-world information is crude information which can be fragmented, boisterous and messy. Thus, information arrangement is utilized to clean information. it comprises of missing value processing, correlation analysis and removing data redundancy

Data Exploration:

a) Find unique number of patient ids to check if a patient has written multiple reviews.

b) Analyze number of drugs per condition by considering condition and number of drugs.

V.RESULTS

A set of experiments carried out on stress analysis data obtained from kaggle.com patients data. The performance evaluation of the system is performing using this dataset. The screenshots of various phases of drugs analysis system are as follows
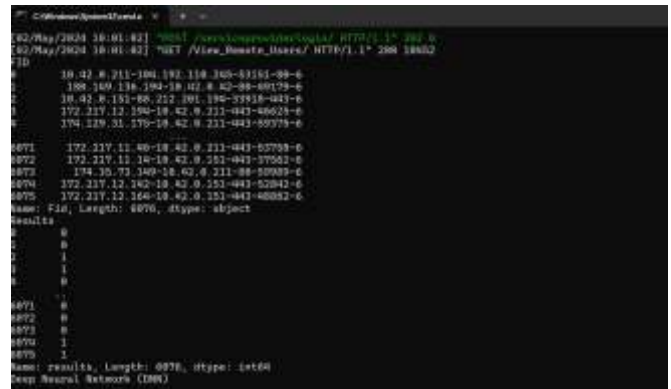
Screen 1:Service Provider Login Page

Screen 2: Prediction of Drugs

Screen 3 : Chart showing Accuracy using various ML Models

Screen 4: Classification Report Showing Precision, Recall and Score values using Naïve Bayes and SVM

Screen 5: Classification Report Showing Precision, Recall and Score values using Logistic Regression

Screen 6: Line Chart

VI.CONCLUSION

AI can help identify the side effects of drugs more accurately, leading to a better understanding of the safety and effectiveness of drugs In this study, we reviewed PV XAI papers and discussed recent research trends and the

need for XAI research. Unlike other areas where XAI and AI are developing together, PV XAI research is still in its infancy. There are not many papers on PV XAI and the methodology is limited to a few models. However, studies are slowly

beginning to show the potential of XAI research for medication monitoring and patient safety, collecting ADR and ADE information, extracting drug-drug interactions, and predicting drug treatment effects.

As in other areas, as awareness of XAI methods grows, we expect to see AI used in pharmacovigilance and

patient safety in many more ways in the coming years than those identified in this review, and the positive

potential of XAI for drug therapy, ADRs and interactions is very promising. However, it is clear that the growth

of this field may be limited by the lack of validated and established uses of XAI in real-world healthcare settings,

and this is an area that requires further investigation. Therefore, the challenges and future prospects of XAIs in pharmacovigilance should be discussed with continued interest.

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