International Journal for Modern Trends in Science and Technology
Volume: 03, Issue No: 08, August 2017
ISSN: 2455-3778
http://www.ijmtst.com

Machine Learning Based Patient Safety Prediction Using Explainable AI in Pharmacoviligence

R.Sivaiah[1]
[1]Computer Science And Engineering, Narayana Engineering College, Gudur, Andhra Pradesh, India

M.Bhavya[2] | K.Mounika[3] | B.Mary Madhuri[4] | T.Naga Bhavitha[5]
[2]Computer Science And Engineering, Narayana Engineering College, Gudur, Andhra Pradesh, India

To Cite this Article
R.sivaiah, M.Bhavya, k.Mounika, B.Mary Madhuri, T.Naga Bhavitha "Research Paper title", *Machine Learning Based Patient Safety Prediction Using Explainable AI in Pharmacoviligence*, Vol. 03, Issue xx, Month Year, pp.-xx-xx.

ABSTRACT

Recently, a number of sectors have emphasized the importance of Explainable AI (XAI), a methodology that supplements the black box of artificial intelligence. Finding studies in the realm of pharmacovigilance utilizing XAI is the aim of this study. Only 25 of the 781 papers that were carefully verified fit the selection requirements, despite numerous prior attempts to choose papers. An intuitive overview of XAI technologies' potential in pharmacovigilance is provided in this article. The included research examined drug treatment, side effects, and interaction studies based on tree models, neural network models, and graph models using clinical data, registry data, and knowledge data. Ultimately, a number of study concerns pertaining to the application of XAI in pharmacovigilance were found to have significant obstacles. XAI is not typically used, despite the fact that artificial intelligence (AI) is actively used in patient safety and drug surveillance, collecting adverse drug reaction data, extracting medication-drug interactions, and predicting effects. As a result, there should be constant discussion about the possible difficulties in using it as well as the opportunities for the future.

KEYWORDS:- ***MACHINE LEARNING, PHARMACOVIGILANCE, EXPLAINABLE ARTIFICIAL INTELLIGENCE***

I. INTRODUCTION

Pharmacovigilance (PV), according to the World Health Organization, is the science and practice of identifying, evaluating, comprehending, and preventing side effects or other drug-related issues. Traditional PV techniques, which can be expensive and time-consuming and can lead to adverse drug reactions (ADRs) that are not reported to medical practitioners, can be effectively supplemented by new artificial intelligence-based technologies. Though its application in PV is still in its infancy, artificial intelligence (AI) has the potential to enhance PV. To better characterize existing pharmacological side effects and reactions and to identify new signals, a variety of machine learning (ML) approaches, together with natural language processing and data mining, can be used to electronic health records, claims databases, and social media data.

Despite having a strong predictive power, AI-based technologies have come under fire for their incomprehensible algorithms. Explainable Artificial Intelligence (XAI) is gaining attention and research because in crucial decision-making domains like healthcare, the rationale behind a choice is just as significant as the choice itself. By evaluating the advantages and disadvantages of current models, XAI aims to foster greater trust and understanding by enhancing the transparency of AI systems and producing explanations for them.

Techniques that remove information from the model's decision-making process, such as post-hoc explanations, might be useful for practitioners and consumers who are more interested in case-by-case explanations than the inner workings of a model. XAI enhances the explainability and transparency of AI systems by making it possible to interpret complex internal features, learned decision paths, and factors that influence decisions within a decision process. I.R. Ward et al. successfully quantified the relevance of attributes using a XAI algorithm, thus demonstrating the potential value of XAI to PV monitoring. In order to ensure medical safety, research and attention must be given to techniques such drug safety reporting and the timely and correct sharing of information on PV activities. PV can help all species affected by medical treatments.

I. BACKGROUND WORK

This study looked at the XAI trend in the PV industry. But the trend was also widely investigated in a wider range of areas, such as interpretable AI. They were thoroughly examined based on the same goal, despite the obvious distinction between Explainable AI (understanding of what various nodes represent and their significance to model performance) and Interpretable AI (capacity to ascertain cause and effect in a machine learning model).
Studies on XAI in drug-related applications have increased dramatically since 2019, with comparatively few studies conducted between 2013 and 2018. More study on XAI in PV applications is needed, as evidenced by the small number of publications. It was challenging to choose relevant search phrases for the investigation of XAI-related studies in PV; we began by hand using general keywords. Pharmacovigilance XAI, pharmacovigilance "explainable artificial intelligence," pharmacovigilance explainable AI, pharmacovigilance explainable ML, and pharmacovigilance explainable machine learning were the five search terms that were conducted. The numbers in parenthesis represent the number of publications that were found using these search terms in a Google Scholar search on June 22, 2022. The final selection of 25 unique publications was achieved by first screening the retrieved articles for titles and abstracts to eliminate duplicates, after which they underwent a first full-text review for relevance and a second full-text review based on a selective technique.
To determine the causal links between medications and adverse drug reactions, PV entails gathering and analyzing data from patient records or other sources. Although clinical data has a lot of potential for monitoring and preventing adverse drug reactions, it can be time-consuming to use since clinical data is frequently kept in several files and has a very varied structure and domain.
Making sense of clinical data also calls for specialized knowledge and frequently knowledge of relevant prescriptions, which typically necessitates extensive preparation with clinical researchers. To determine the causal links between medications and adverse drug reactions, PV entails gathering and analyzing data from patient records or other sources.
Although clinical data has a lot of potential for monitoring and preventing adverse drug reactions, it can be time-consuming to use since clinical data is frequently kept in several files and has a very varied structure and domain. Furthermore, interpreting clinical data necessitates specialized knowledge and frequently calls for knowledge of relevant prescriptions, which typically calls for extensive planning.

II. DESIGN

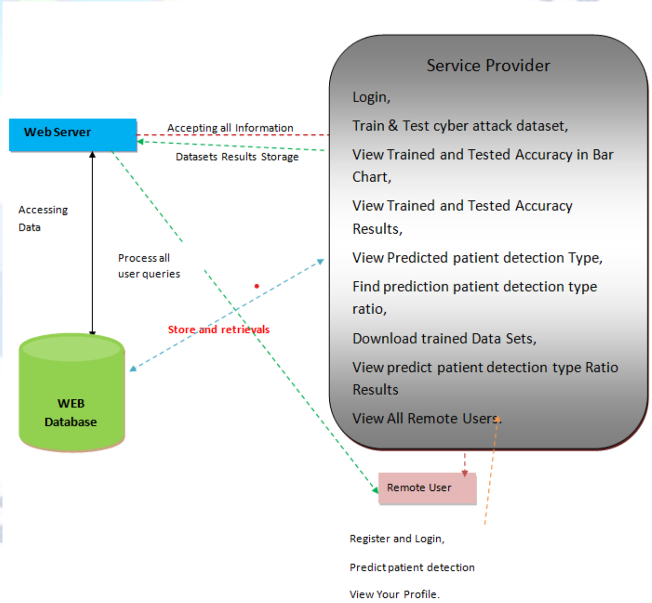

Fig.1 System Workflow.

III. WORKING

Service Provider

✓ The Service Provider must use a valid user name and password to log in to this module. He can perform many tasks after successfully logging in, including browsing datasets and training and testing datasets. See the prediction of patient safety type, see the predicted patient safety type ratio, download the predicted data sets, and view the trained and tested accuracy in a bar chart. View All Remote Users and the Predicted Patient Safety Type Ratio Results

Train and Test Model

- ✓ The service provider divided the used dataset in this module into 70% train data and 30% test data, accordingly. Thirty percent of the data is regarded as test data, which is used to evaluate the model, and seventy percent is regarded as train data, which is used to train the model.

Remote User

- ✓ A total of n users are present in this module. Before beginning any operations, the user should register. Following registration, the user's information will be entered into the database. Following a successful registration, he must use his password and permitted user name to log in. Following a successful login, the user can perform tasks like VIEWING YOUR PROFILE, PREDICTING PATIENT SAFETY DETECTION, and REGISTERING AND LOGINING.

Classification

- ✓ This module allows users to submit data and utilize machine learning models that have been proven to be effective in classifying it.

Algorithms Used

Support Vector Machine

- Support-vector machines (SVMs, also known as support-vector networks) are supervised learning models in machine learning that use related learning methods to examine data for regression and classification. As a non-probabilistic binary linear classifier, an SVM training technique creates a model that allocates new samples to either category.

Gradient Boosting Classifier

- Using gradient descent, each new model is trained to minimize the loss function, such as mean squared error or cross-entropy of the prior model. Gradient Boosting is a potent boosting approach that turns multiple weak learners into strong learners. The algorithm calculates the gradient of the loss function in relation to the current ensemble's predictions in each iteration, and then trains a new weak model to minimize this gradient. The process is then continued until a stopping requirement is satisfied after adding the new model's predictions to the ensemble.

Random forest

- It creates a number of decision trees, each of which makes a prediction based on a portion of the data sample.
- The outcome that the greatest number of trees were able to produce is then regarded as the final forecast.
- A supervised learning algorithm called Random Forest employs the ensemble learning approach for regression and classification. A bagging technique, random forests have trees that operate in parallel without interacting with one another.
- During training, a Random Forest builds many decision trees, with the mean of the classes serving as each tree's prediction.

Decision Tree

- Decision trees are supervised learning methods that are mostly used to solve classification problems, while they can also be used to solve regression problems.
- This tree-structured classifier is a graphical depiction of all the potential solutions to a problem or decision based on specified conditions, with internal nodes representing the dataset's features, branches representing the decision rules, and each leaf node representing the result.

Logistic Regression

- Among the most widely used machine learning algorithms, logistic regression falls under the category of supervised learning. With a given collection of independent factors, it is used to predict the categorical dependent variable.
- A categorical dependent variable's output is predicted by logistic regression. As a result, the result needs to be a discrete or category value. Yes or No, 0 or 1, true or false, etc., can be used, but probabilistic values that fall between 0 and 1 are provided rather than the precise values of

0 and 1.

IV. Results

Fig.2 Home Page

Fig.3 Service Provider Login

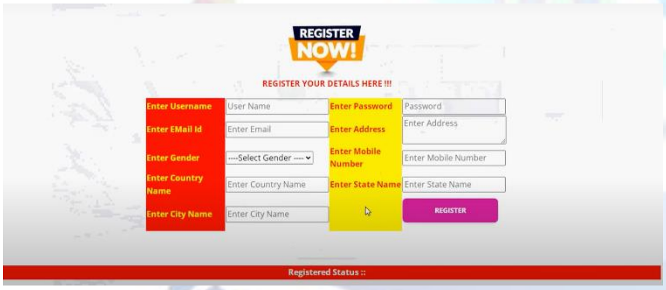

Fig.4 Remote User Registration

Fig.5 Predict Patient Safety Detection

V. Conclusion

In this study, we examined literature on PV XAI and talked about the necessity for XAI research as well as current research trends. Research on PV XAI is still in its early stages, in contrast to other fields where XAI and AI are co-developing. The methodology is restricted to a few models, and there aren't many studies on PV XAI. The promise of XAI research for medication monitoring and patient safety, gathering ADR and ADE data, extracting drug-drug interactions, and forecasting the effects of therapeutic treatments is, nevertheless, just now starting to be demonstrated by studies. As in other fields, growing awareness of XAI techniques, The positive potential of XAI for medication therapy, adverse drug reactions, and interactions is quite promising, and we anticipate seeing many more applications of AI in pharmacy vigilance and patient safety in the years to come than those mentioned in this review. However, it is evident that the absence of proven and validated applications of XAI in actual healthcare settings may restrict the field's progress, and this is an area that needs more research.

VI. Reference

[1] World Health Organization. (Oct. 2004). WHO Policy Perspectives on Medicines. Looking at the Pharmacovigilance: Ensuring the Safe Use of Medicines.

[2] J. K. Aronson, "Artificial intelligence in pharmacovigilance: An introduction to terms, concepts, applications, and limitations," Drug Saf., vol. 45, no. 5, pp. 407–418, May 2022, doi: 10.1007/s40264-022-01156-5.

[3] P. G. Dal, R. Ball and, "'Artificial intelligence' for pharmacovigilance: Ready for prime time?" Drug Saf., vol. 45, no. 5, pp. 429–438, 2022.

[4] T. Wiegand, and K.-R. Müller, W. Samek, "Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models," 2017, arXiv:1708.08296.

[5] D. Aha, D. Gunning and "DARPA's explainable artificial intelligence (XAI) program," AI Mag., vol. 40, no. 2, pp. 44–58, 2019, doi: 10.1609/aimag.v40i2.2850.