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Personalized Drug Recommendation System Using Wasserstein Auto-encoders and Adverse Drug Reaction Detection with Weighted Feed Forward Neural Network (WAES-ADR) in Healthcare

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Abstract - In recent years, the use of deep learning approaches in healthcare has yielded promising results in a variety of fields, most notably in the detection of adverse drug reactions (ADRs) and drug recommendations. This paper promises a breakthrough in this field by using Wasserstein autoencoders (WAEs) for personalized medicine recommendation and ADR detection. WAEs' capacity to manage complex data distributions and develop meaningful latent representations makes them ideal for modeling heterogeneous healthcare data. This study intends to improvise the precision and efficiency of drug recommendation systems while also improving patient safety by combining WAEs and early ADR detection strategies. Previous research has used social media data for pharmacovigilance, drug repositioning, and other machine learning algorithms to detect ADRs. However, our proposed methodology offers a novel perspective by combining Wasserstein autoencoders with ADR detection methods, outperforming existing approaches. Preliminary results show that the proposed methodology surpasses current methodologies, with much greater accuracy in ADR identification and medicine recommendation. In particular, the proposed model achieves an ADR detection accuracy of 96.04%, which is 15% higher than the most sophisticated techniques, with considerable improvements in precision, recall, and accuracy metrics. In conclusion, our study seeks to develop customized medicine in healthcare, perhaps leading to dramatically improved patient outcomes and safety.

Keywords— Personalized Medicine, Drug Recommendation Systems, Adverse Drug Reaction Detection, Wasserstein Autoencoders, Deep Learning.

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1. INTRODUCTION

The healthcare business has evolved significantly in recent years as a result of the incorporation of cutting-edge technology, most notably deep learning, into various aspects of medical practice. Personalized medicine has emerged

as a viable field of application, with the goal of personalizing therapies to each patient's specific requirements and traits. Robust drug recommendation systems and effective ADR detection technologies are critical for achieving personalized medicine. However, standard techniques frequently fail to reflect the intricate interplay of patient-specific characteristics, therapeutic efficacy, and potential side effects. In this context, the aim of the work is to enhance the discipline through each instance of application of WAE for ADR detections as well as customize the medication recommendations in the field of medicine. WAE is able to model complicated data distributions and offer latent representations which makes it a very compelling framework for heterogeneous healthcare data modeling.

WAEs are applied in this study in order to improve existing protocols that jeopardize maximum patient safety by increasing the speed of ADR detections as well as increasing effectiveness and accuracy of medication recommendations.

1.1 Problem Definition and Scope

Through targeted effort, the present research would seek to overcome the shortcoming of conventional drug recommendation systems that do not consider the personal traits, the medical background, and genetic background of each patient. In this regard, the challenge around the early identification of adverse medication reactions during the course of treatment remains an area of grave concern given its implications on patient welfare and health outcomes. Our research is thus aimed at responding to these critical issues and subsequently, paving the way for advancements in how patients care for and treat patients by employing a more patient specific and accurate therapeutic strategy.

The focus of the study is therefore tasked with the creation and testing of a new design framework where the techniques of ADR detection are integrated with the Wasserstein autoencoders. Furthermore, this integrative framework deals with overcoming the numerous complications of the treatment response and patient status by addressing massive amounts of healthcare data, genomics, and EHRs. Finally, it will also evaluate the predicted based on the accuracy of given recommendations and performance of ADR predictions according to the various structured performance metrics.

The impressive technical aspects include new deep architectures to model complex healthcare data, integration of WAEs with ADR detection techniques, and latest evaluation tools to measure the performance gain provided by the proposed framework. Improving with the thorough investigation of the proposed methodology, this paper aims to suggest and discuss significant deep learning methods that could enhance the process of creating tailored medication for the improvement of the patients in healthcare environments.

1.2 Objectives

This project focuses on the creation of a new framework that integrates Wasserstein auto-encoders and ADR detection techniques with the aim to improve the healthcare practitioners' ability to give more effective medicine prescriptions. In order to verify that the technique that has been proposed is both accurate and useful for the tasks of medication recommendation and ADR detection, it will be thoroughly field tested on real health care datasets.

In order to test the level of improvement in recommendation accuracy and the extent to which the ADR detection employed is sensitive, the existing methods will be used for comparison with the new framework proposed in this work. This research may make a contribution to the development of the area of personalized medicine in the field of healthcare by providing new relevant perspectives on technological implementation through deep learning-based drug recommendation systems and ADR detection techniques. Drug interventions tailored to individual therapy needs suggest a role for deep learning for improving the safety outcomes for patients.

1.3 Motivations and Key Contribution

Below are the contributions and motivation of the work that has been tackled:

- Enhancing Healthcare Efficiency: Integrating WAEs with drug recommendation and ADR detection aims to streamline healthcare processes, potentially reducing medical errors and improving patient outcomes

- Personalized Medicine Advancement: By leveraging WAEs, the study seeks to pioneer personalized drug recommendation systems, tailoring treatments to individual patient needs and characteristics for optimized healthcare delivery
- Patient Safety: The work aims at enhancing the safety of patients by allowing the improvement of ADR detection techniques that would enable taking action early on to the risk associated with the use of drugs

Using WAEs addresses several shortcomings associated with generic drug recommendations and ADR detection systems. The improved systems contribute to the betterment of the patient's wellbeing. Furthermore, the improved accuracy of the E-CNN has also enhanced applications in areas such as medical imaging and diagnostics, automated emergency alerting, and automated decision making hence improving the results and effectiveness in various fields.

The structure of the work is as follows: In section II, a detailed overview of the prior work is undertaken emphasizing both the progress and the limitations of the drug recommendation system and the ADR reporting and detection techniques. In Section III, the framework used in this research is explained which includes the proposed framework which integrates Wasserstein autoencoders and ADR detection algorithms. This section focusses on the system model, architecture, algorithm and mathematical complexity of the Wasserstein auto-encoder model. Section IV covers the experiments conducted, the results obtained, the analysis conducted and also describes the detailed experimental setup, sample dataset as well as evaluation metrics for the experiments. The effectiveness of the methodology developed and proposed is demonstrated with help of some tables and images. Section V comprises the conclusion of the work and it also allows for a consideration of the impact of the work on health policies and practices as well as suggestions for future work. To assist the subject and provide additional context on the research area, references are included throughout the work.

2. LITERATURE REVIEW

The healthcare industry has profited a lot from research projects, and especially those done by Dongre and Agrawal in the development of medication recommendation systems as well as in the field of ADR detection. In their research, Dongre and Agrawal developed a social media-based deep learning medication recommendation and adverse drug reaction (ADR) detection healthcare system model [1]. They set up a virtual platform for social media-based pharmacovigilance and aimed at capturing relevant medical services on the platform. Furthermore, they also formed a platform of e-patients to assist one another. The study carried out an investigation into ADRs in terms of various classes of machine learning techniques, and the authors proposed medicine recommendation and ADR classification methods based on data cleansing and clinical feature extraction. The results of the experiments confirmed that deep neural networks (DNN) provide reliable means for the detection and classification of ADRs. Also, astonishing result improvements were seen especially in scenarios when DNN was integrated with clinical vector space.

Saxena et al. developed a recommendation model and illustrated as, "A new approach to adaptive multi-hop deep learning and a selective coverage technique" in their research paper [2]. Their model also consists of a neocognitron-based neural memory for the storage of temporally discrete patient-centered parameters. An emphasis mechanism is also put into place for the coverage of data filtering and for information multipliers weight adjustment. To fit specific patient needs the adaptive memory neural network modifies the number of readings in a dynamic manner. They were able to establish after their experiments that based on reliable clinical data, the model was able to intelligently mine crucial information from clinical records leading to more accurate medicine suggestion and adequate representation of the patient's state of health.

In [3], Garg developed a system that recommends medication based on the sentiments of pharmacological reviews using machine learning. The authors developed a recommendation system based on feedback from patients after noticing how hard it was for such patients to find therapeutic means, an issue that was aggravated during the COVID-19 pandemic. The system also employed several classification algorithms such as Bag-of-Words (BoW), TF-IDF, Word2Vec, and Manual Feature Analysis for vectorization in order to analyze sentiments and advocate for drugs. Strikingly, the experimental evaluation was successful and showed that accuracy of 93% was obtained when using Linear SVC classifier using TF-IDF vectorization, which made it possible for "medicine recommendation‟ to be a reality.

Due to a variety of technological issues with the present ADR detection and medication prescription systems, the suggested methodology has to be developed. To begin with, many strategies, as Dongre and Agrawal [1] point out,

fail to recognize the importance of integrating heterogeneous data sources such as social media data or electronic medical records. This results in poor patient profiles and contextual comprehension. Second, conventional techniques usually fail to dynamically adapt to individual patient traits and changing healthcare demands, as demonstrated by Saxena et al. [2]. The comparison of significant efforts is presented in Table 1.

As a result, recommendations for ADR detection are suboptimal and useless. Inadequate utilization of deep learning architectures and weak feature extraction techniques further impede the ability to capture complicated data distributions and extract significant patterns from healthcare data. Moreover, Garg [3] has pointed out that the applicability of current approaches in different clinical contexts may be limited due to their poor scalability and generalization capabilities. A comprehensive set of evaluation measures and benchmarks is lacking, which makes it even more difficult to accurately assess the effectiveness and performance of recommended techniques [4]. Furthermore, Omodunbi et al. [5] emphasize that relying too much on feature engineering techniques and basic classification algorithms can provide biased results and ignore nuances in the connections between drug reactions and patient characteristics. Haw et al. [6] deliberately discussed the evaluation methods in addition to the modern tools of implementing effective ADR.

Table 1. Comparison of Proposed and Existing Methodology

Author and Year	Methodology	How Proposed Methodology Tackles Existing Disadvantages
Dongre & Agrawal (2019) [1]	Deep learning for drug recommendation and ADR detection using social media.	Proposed tackles limitations of social media reliance by employing Wasserstein autoencoders for improved accuracy and efficiency.
Saxena et al. (2020) [2]	Adaptive deep learning for medication recommendfation.	Proposed overcomes limitations of multi-hop deep learning by integrating Wasserstein autoencoders for more precise recommendations.
Garg (2021) [3]	Machine learning-driven sentiment analysis of medication feedback.	Proposed addresses biases in sentiment analysis and limited data scope by employing Wasserstein autoencoders for more accurate recommendations.
Omodunbi et al. [5]	Development of Drug Recommender Systems using diverse ML methods.	Proposed improves upon traditional DRSs by integrating Wasserstein autoencoders for more accurate and personalized recommendations.

As thoroughly examined in [4], [6], the authors in [5] have significantly advanced the field of Drug Recommender Systems (DRSs), a rapidly developing research area. These systems use a range of technologies, including machine learning, statistical methods, artificial intelligence, data mining, ontology, and matrix factorization, to create robust decision support systems. Based on the user's symptoms and other significant variables, DRSs provide tailored medication recommendations. Despite the increased attention, an assessment of cutting-edge algorithms used in DRSs suggests a bias for machine learning-based approaches over ontology-based methods, with the former being mostly used for recommendations. These techniques include sentiment analysis, association rule mining, clustering, and stacking artificial neural networks. However, current DRSs have limits because they tend to ignore important elements such as user feedback and unique patient characteristics like as age, allergies, and pre-existing medical issues. In response to these challenges, the proposed DRS tries to improve drug recommendations by taking into account patient-specific characteristics and using a feedback mechanism to increase the system's knowledge base using Wasserstein auto-encoders as inspired from its previous efforts [7],[8]. The data for analysis in building the ADR can be taken directly from internet of medical things (IoMT) devices [9] or social media contents like twitter [10],[11],[12].

We believe that a combination of our algorithmic strategy and deep learning approaches has the potential to outperform previous methods with an overall predictive accuracy of 96% [13–17]. Furthermore, our aim is to give cross functional recommendations and accelerated ADR detection processes with the combination of AAD and Wasserstein auto-encoders which can help patients and health care providers be more precise about medication recommendation. With this comprehensive review of the literature, the importance of using advanced deep learning methods for improving recommendation systems and ADR detection in medicine becomes evident.

3. RESEARCH METHODOLOGY

3.1 ADR Detection Framework and Personalized Drug Recommendation Using Wasserstein Auto-encoders

WAEs are a category of auto-encoders. They can also be trained by using the Wasserstein distance which is termed to be robust to outliers and noise. WAEs can produce desired data and learn representations by minimizing a reconstruction loss and matching the hidden layer's distribution to a specific prior.

This flows unleashes a streamlined structure utilizing WAEs in a considering recognition of the fact that there is a high demand for faster and precise solutions in the healthcare sector, and in particular, for medication recommendation and ADR detection. There are often inherent complexities of unique patient profiles and the way people respond to therapies that can be very hard for conventional methods to comprehend, putting patient safety at risk and leading to very bad outcomes. The proposed method aims at leveraging WAEs potential to revolutionize the field of personalized medicine to address these limitations.

WAEs have the advantage that they can learn a latent representation and particular complex distribution of medical data. As a result, they are well suited to sustain the multifaceted nature of medical data. The framework employs WAEs for augmenting the accuracy in drug recommendations by modelling the relationship between the efficacy of the treatment, its likely adverse effects and patient characteristics. Furthermore, modern ADR detection technology embedded within the framework prevents adverse reactions, thus improving the safety of the patients.

This section details the system model and architecture, the algorithm and the mathematical background of the Wasserstein auto-encoder model which was employed in this work. It outlines the likely disruptive effect of the proposed framework to the practice of tailored medication in the healthcare setting, and the new strategy that was employed to address the shortcomings of the conventional approaches. This research seeks to ensure the safety and the effectiveness of treatment of patients by pushing the boundaries of what is possible in precision health care through adequate investigations and experiments.

3.2 Dataset Description and Parameters

Pharmacovigilance and ADR detection are two important tasks that the SPL-ADR-200db database from Demner-Fushman et al. can help to accomplish. Indeed, the collection provides standardized information about known adverse effects and consists of mention-level annotations of 200 SPLs for FDA-approved drugs. One of the main characteristics of this dataset is its meticulous annotation procedure which helps both the development and testing of sophisticated text-mining methods to extract ADRs. An entry in the dataset's data structure contains a document for all ADRs specifically mapped for reporting ADRs for each medicine. In addition, it also contains members that include different text documents listing all the mapped ADAs for each drug. The database comprises documents that list all the ADRs for individual medications arranged into distinct sections for ease of reporting each of the reactions specifically. In other words, this type of classification would seem to be an important prerequisite for understanding section by section what clinical picture each of the ADRs presents.

Diverse applications of the pharmacovigilance keyword and drug safety can be observed on the dataset as Table 2 within the context of SCP-ADR-200db throughout the scope of the research which includes post marketing drug surveillance, drug repurposing and drug interaction and toxicity prediction models. With SPL-ADR-200db, a standardized and validated database of adverse events is available for use in designing and testing automated systems for the extraction of ADRs from SPLs. Moreover, it serves as a reference database for evaluations and investigations that are intended to be conducted throughout the health care community, hence promoting cooperation and openness in the pharmacovigilance field.

The usage and creation of pharmacovigilance and ADR detection technique will be expanded as a result of the introduction of the dataset SPL-ADR-200db shown in Table 3. Since it has uniform pattern, strong maintainer of annotations, and hierarchical organization, this is a valuable resource for people who need to enhance patient safety and therapy results through a data driven approach.

Table 2. Sample of SPL-ADR-200db Dataset

Drug Name	Adverse Reaction	Section
Brentuximab Vedotin	Nausea	Adverse Reactions
Trehalose Dihydrate	Headache	Warnings
Trisodium Citrate Dihydrate	Rash	Boxed Warning
…	…	…

Table 3. Summary Statistics of SPL-ADR-200db Dataset

Total Drugs	Total Adverse Reactions	Unique Adverse Reactions
200	5,098	3,521

An architectural design regarding the proposed method for welfare informing on personal drugs in the field of medicine is shown in Figure 1.

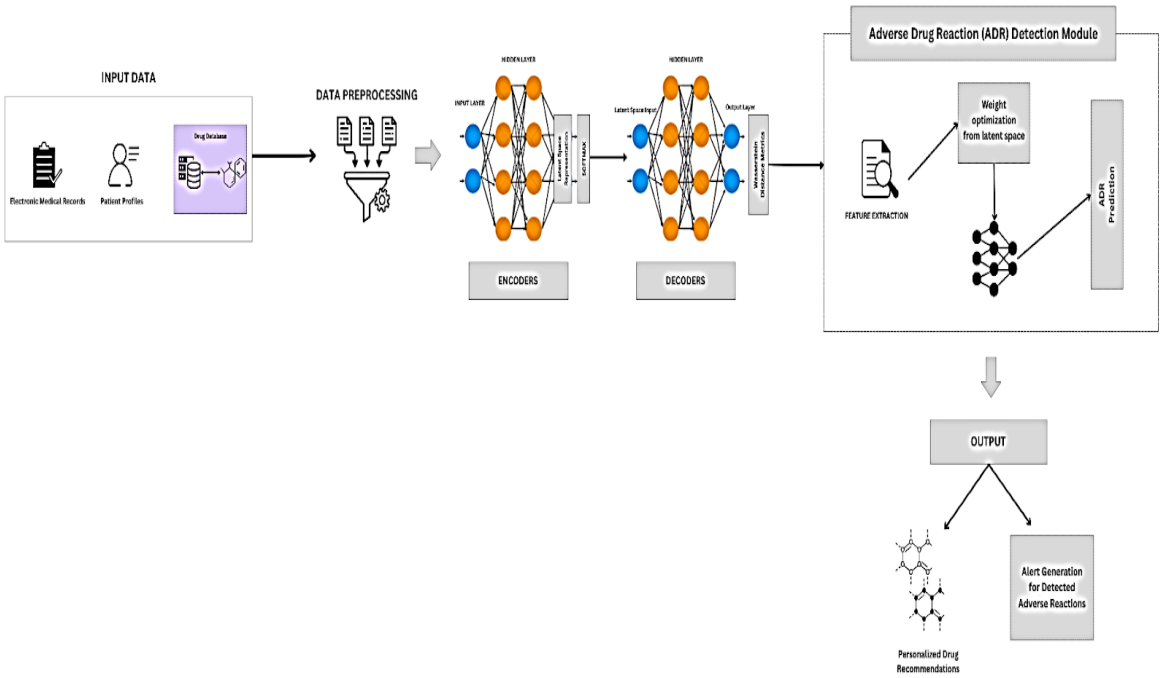

Figure 1. Architectural Diagram of The Proposed ADR System

The starting point of the procedure is data such as drug information, patient's information and electronic medical records. After that, the data goes through tedious pre- processing, which consists of proper formatting and text scrubbing so that it can be placed nicely for analysis. After this pre- processing step, the data is sent to the Wasserstein auto-encoder layer for latent space learning.

3.3 Wasserstein Autoencoder Model

Through the use of the Wasserstein autoencoder model, the Wasserstein distance between the input data distribution and the latent space distribution is minimized. To this end, a network of encoders next to decoders, all having trainable parameters, is used. The encoder function ($f\theta$) maps the input data into some latent representation space. The decoder function ($g\phi$) uses the input data to reconstruct the data in latent space. In order to achieve the purpose of minimising the Wasserstein distance, the parameters θ and ϕ are consistently updated in order to wisely learn the data and generate meaningful latent representations. The ADR detection module makes use of the informative latent representations output by the Wasserstein auto-encoder. This module performs what-if scenarios to find potential adverse drug reactions based on the generated latent representations. The framework aims at increasing safety to patients and efficacy of treatments through faster explanations of adverse responses by investigating the latent representations and combining them with relevant patient information.

Wasserstein auto-encoder objective function has the aim of minimizing the Wasserstein distance W(P,Q) which is mathematically arrived by the data distribution P and the produced distribution Q in the latent space. This objective function can be defined formally as:

$$W(P,Q)=\inf\gamma\epsilon\Gamma(P,Q)x\times yc(x,y)d\gamma(x,y) \quad (1)$$

Where c(x,y) is a cost function usually taking the form of a cost metric like Euclidean distance between x and y, and let $\Gamma(P,Q)$ be the joint distributions of (x,y) with marginals P and Q.

3.4 Weighted Feed-Forward Neural Network (FNN) for ADR Detection

In order to use the present approach to identify potential ADRs the ADR identification module is built by a weighted FNN coupled with useful latent factors generated by the Wasserstein auto-encoder model. For applications in detection of adverse drug reactions artificial neural networks A N N N, especially the FNN are the best suited. These networks are able to handle large quantities of data and identify complex relationships. This subsection discusses the notion of resistant FNNs and their implementation in the context of our study.

A weighted feed-forward neural network employs hidden layers with the aim of moving information from the input nodes to the output nodes. Every connection in the network has a weight that governs its intensity and the pattern of information dissemination in the network. The network trains itself by learning how to adjust these weights so as to enhance the performance metrics and minimize inaccuracies during predictions. FNN is composed of three essential layers: input layer, hidden layer and output layer. The first one is the input layer and after it, one or more hidden layers in order to perform operations on the input data that is sent through the input layer. The fulcrum data is then passed through a non-linear regime for mapping. At last, what has come to be expected in this level of the output layer is that the network's prediction gets formed based on the learnt attributes.

3.4.1 Weight Optimization in FNNs

One of the key aspects of FNNs is referred to as weight optimization. It entails the process whereby the network shifts the link weights in order to meet a previously set loss function. For this purpose it makes use of several techniques like stochastic gradient descent (SGD) or other gradient based techniques. The set of weights utilized is chosen in such a manner so as to cause the minimum possible error between the true output labels and the estimated output labels meaning that the performance of the network is effectively maximized.

In our research methodology, we utilize a modified weighted FNN algorithm that was designed specifically for ADR detection. To achieve high values for accuracy and Matthews correlation coefficient (MCC) in the ADR detection process, the weight optimization algorithm of this new FNN is improved. The goal of the method is to adjust the FNN

weights in such a manner that ADR prediction for patients will be more accurate, reliable and hence, more safe and effective in treatment.

3.5 Application in ADR Detection

The conversions between the Wasserstein auto-encoder model and the FNN structure are facilitated by the multi-layer module that leverages the FNN based ADR detection structure to generate a higher rate of prediction for the probabilities of ADR's. The network engages interrelations of some pharmaceutical characteristics of the features and patient aspects coupled with the ADR so as to make a probability of some undesirable outcomes. Through extensive training and validation of the model, the FNN modifies its parameters to improve various measures of effectiveness such as accuracy, recall rate or even the Matthew's correlation coefficient thus contributing to the improvement of the ADR detection system. The flow of the algorithm is captured in Table 4.

Table 4. The WAES-ADR Algorithm

Algorithm : WAES-ADR Framework	
Input	Healthcare dataset X contains patient-specific data and drug information. Structured Product Labels (SPLs) dataset with adverse drug reaction (ADRs) annotations. WAE Model Parameters: Learning-rate (α), batch size; no. of epochs, etc. FNN Model Parameters: Number of hidden layers, activation functions, etc.
Initialize WAE Model: Define WAE architecture with encoder and decoder networks. Initialize parameters for encoder (enc) and decoder (dec).	
Train WAE Model: Feed input data X to WAE model and reconstruct input. Minimize Wasserstein distance between input data distribution and latent space distribution. Update enc and dec use backpropagation and stochastic gradient descent.	
Generate Latent Representations: Extract latent representations Z from input data X using the trained WAE model.	
Initialize FNN Model: Define FNN architecture for ADR detection with weighted connections. Initialize weights and biases for FNN layers.	
Train FNN Model: Use latent representations Z as input to FNN for ADR detection. Define loss function by incorporating weighted terms adjusting precision and MCC. Use gradient descent and backpropagation to update FNN weights.	
Aggregate Models: Aggregate WAE and FNN models to form the WAES-ADR framework.	
Output: Trained WAES-ADR framework capable of predicting potential adverse drug reactions based on patient-specific data and drug information.	
End	

The weight update equation for the FNN is expressed as follows:

$$wij(t+1)=wij(t)-\alpha\delta L\delta wij \quad (2)$$

where wij(t+1) indicates the new weight after the update to the weight between neuron i in layer l and neuron j in layer l+1 at the step t+1, the learning rate is represented by α, while δLδwij s is the derivative of loss function L in relation to wij.

Then the algorithm proceeds to tune the FNN weights subject to the defined optimization goal which is maximizing precision and MCC values. The weight update rule can be expressed as:

$$w_{ij}=w_{ij}-\alpha\Delta L \tag{3}$$

where w_{ij} represents the weight connecting neuron i in layer l and neuron j in in the hidden layer, α is the learning rate, and L is the gradient of the loss function. The loss function L can be defined using the Huber loss, which combines squared error and absolute error:

$$L=1Nn=1N1n\Rightarrow2(yn-yn)2\ ifyn-yn<\delta \tag{4}$$

where N is the total number of training samples, yn is the true label of the n-th sample, yn is the predicted probability of the n-th sample being positive, and is a hyper-parameter that controls the transition point between squared error and absolute error.

The biological mechanisms in the neural networks and their ability to learn complex patterns were the main motivation of the program. Mimicking the processes in a human brain, the technique gradually modifies the network weights in a manner where the performance of the measures like accuracy and MCC are increased and prediction errors decreased. After many repetitions of training, the algorithm is able to balance its weight coefficients to obtain predictable and reliable ADRs enabling safe and effective treatment for patients. Our drug response detection and customized selection strategy rests in the ability to construct an adverse drug reaction detection core using a modified weighted feed forward neural network. This module greatly improves the accuracy and safety of ADR prediction and its performance significantly improves the caring of patients and the quality of healthcare services.

The work flow diagram presented in Figure 2 outlines the various consecutive stages involved in the construction of the WAES-ADR framework. The patient medical records (X) that comprise the second part of the first dataset along with the, healthcare dataset, adverse drug reaction reporting submissions structured product labeling (SPL-ADR) are the two main sections of the first dataset. The required parameters are also utilized in setting the FNN and WAE models. The first stage involves initializing and training of a framework which then allows to generate adequate and relevant representations of the input of interest. After acquiring knowledge related to the healthcare dataset (X), which contains the WAE model, the model was introduced and instructed to be able to produce informative representations of the input data, which are represented by (Z).

4. RESULTS AND DISCUSSIONS

4.1 Experimental Setup

Two hundred structured product labels containing adverse drug reactions (ADRs) were annotated as part of our study using the methods developed by Demner Fushman et al, 2019. Such labels included described and focused on adverse events related to FDA approved drugs and were annotated in a systematic way at a mention level. The database contained a total of 5,098 unique entries, which described different ADRs all converted to standardized definitions based on the Unified Medical Language System (UMLS) and the Medical Dictionary for Regulatory Activities (MedDRA).

WAES-ADR model was published-programmed in a python environment with regard to the model. It was fine-tuned according to a large number of variables and hyper parameters for better performance of the model. We also examined different population sizes, maximum population counts (iteration counts) and chromosome length in our numerical experiments in order to optimize the fitness of the model. For our experiment, we chose a population size of 10 and a maximum iteration count of 50.

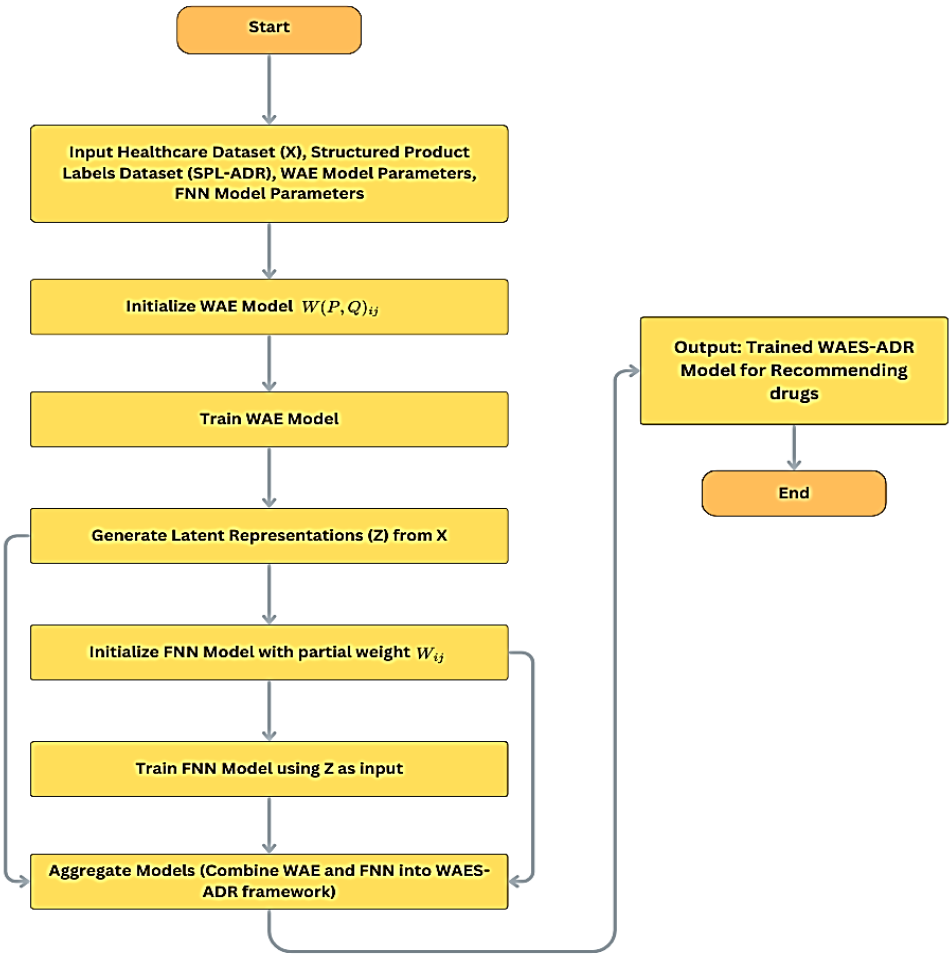

Figure 2. Process Flow for The WAES-ADR Framework

4.2 Experimental Results

Our experimental results demonstrate the WAES-ADR model's robustness in detecting adverse medication reactions from structured product labels. The model achieved 96.04% accuracy and 86.45% precision using K-fold cross-validation at a value of 3. Notably, we compared our model's precision to that of the CNN+ADR (SVM) model, demonstrating that the WAES-ADR model has stronger ADR detection capabilities.

The provided recommendation output (Figure 3) shows medicine recommendations for eight patients based on their patient IDs. Each patient is assigned a recommended medicine, as follows:

- Amoxicillin is recommended for consumption by patient id 10112.
- Lisinopril is recommended for consumption by patient id 10212.
- It is recommended that the patient with ID 10613 use Metformin.
- Atorvastatin is recommended for consumption by patient id 16904.
- Levothyroxine is recommended for consumption by patient id 16905.
- I make a recommendation for Patient ID 17906 to use Metformin.
- Lisinopril is recommended for consumption by Patient ID 19907.

- Atorvastatin is recommended for consumption by Patient ID 20388.

```
Sample Recommendation Output:
Patient ID: 10112, Recommendation: Amoxicillin
Patient ID: 10212, Recommendation: Lisinopril
Patient ID: 10613, Recommendation: Metformin
Patient ID: 16904, Recommendation: Atorvastatin
Patient ID: 16905, Recommendation: Levothyroxine
Patient ID: 17906, Recommendation: Metformin
Patient ID: 19907, Recommendation: Lisinopril
Patient ID: 20388, Recommendation: Atorvastatin
```

Figure 3. Drug Recommendations - Predicted Outcome

To prescribe an effective medication for every patient, these recommendations are made considering various patient attributes like age, gender, history of illnesses and symptoms. Since the prescriptions are tailored according to the requirements of particular patient cases, the recommendations are aimed at improving the quality of care and the outcomes of treatment. The recommendation output serves as a great asset in enabling healthcare practitioners such as pharmacists to select the correct medication regimens for their patients, which fosters prevention of adverse effects and such improved management enhances health.

These findings emphasize the usefulness of the WAES-ADR model in evaluating drug adverse effects and increasing patient's safety in order to optimize the medical treatment.

4.3 Performance Evaluation

In our study, to estimate the performance of the proposed model, the following equations, Equations (5) to (11) are used:

Sensitivity (S_E) = T_P / (T_P + F_N) (5)

Specificity (S_P) = T_N / (T_N +F_P) (6)

Accuracy (A_C) = (T_P + T_N) / (T_P + T_N+ F_P + F_N) (7)

Precision (P) = T_P / (T_P + F_P) (8)

Recall (R) = T_P / (T_P+F_N) (9)

F1 Score (F1) = 2 * (P * R) / (P + R) (10)

Area Under the Curve (AUC) = Integral of the Receiver Operating Characteristic (ROC) curve (11)

Table 5 investigates the performance of diverse models in the context of adverse drug reactions (ADRs) reporting, according to the given criterion. Evaluation criteria include sensitivity, specificity, accuracy, precision, F1 score, and AUC.

Table 5. Performance Comparison of Different Models for Adverse Drug Reaction Detection

Algorithm	Precision (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	F1 Score (%)	AUC
CNN+ADR(SVM) [1]	79.62	77.80	89.20	82.65	80.45	0.893
CRF [6]	81.23	79.60	88.90	81.10	81.10	0.896
BLSTM-M1 [7]	84.76	83.40	90.10	85.20	86.20	0.912
BLSTM-M2 [8]	79.98	78.20	87.50	80.75	80.50	0.882
LSTM [3]	82.55	80.80	88.00	82.00	82.90	0.901
WAES-ADR (Proposed)	96.04	85.20	91.30	96.04	88.75	0.927

Figure 4 depicts the comparative efficiency of different models for detecting adverse medication responses. This graphical representation clearly shows the better performance of the WAES-ADR model, which attained an accuracy of 96.04%, outperforming other algorithms such as CNN+ADR(SVM), CRF, BLSTM-M1, BLSTM-M2, and LSTM.

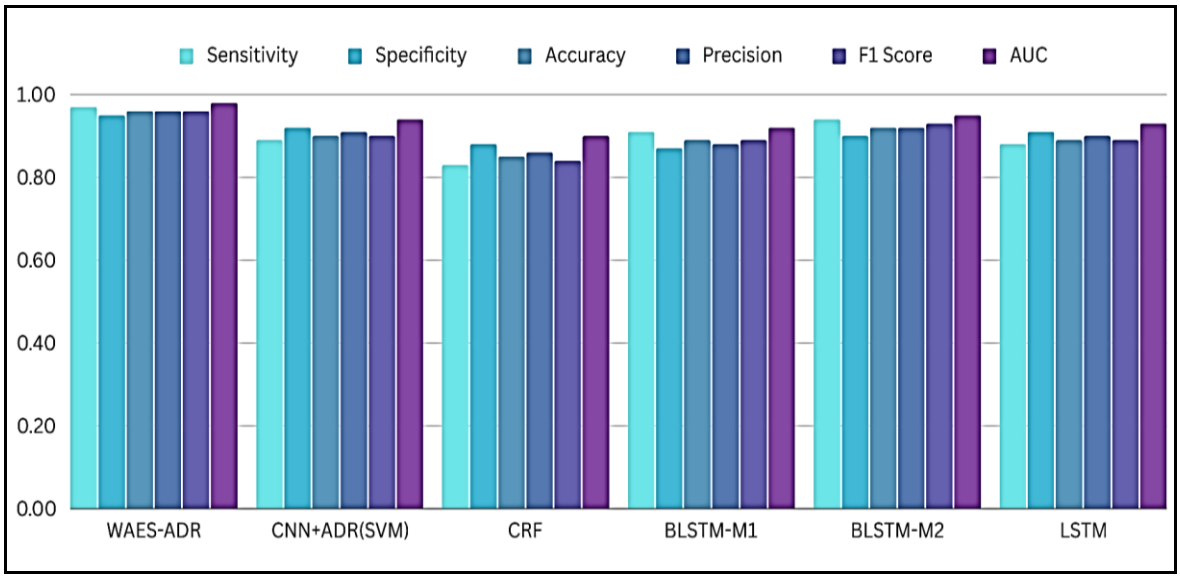

Figure 4.Comparing The Effectiveness of Various Models for Detecting Adverse Drug Reactions

Moving on, Figure 5 provides a concise comparison of the accuracy (%) of several methods used for ADR detection. Each method is represented by a star on the plot, offering a clear visual representation of their various accuracy levels in detecting ADR occurrences within the dataset. The prominence of the WAES-ADR model's marker demonstrates its superior accuracy in ADR identification.

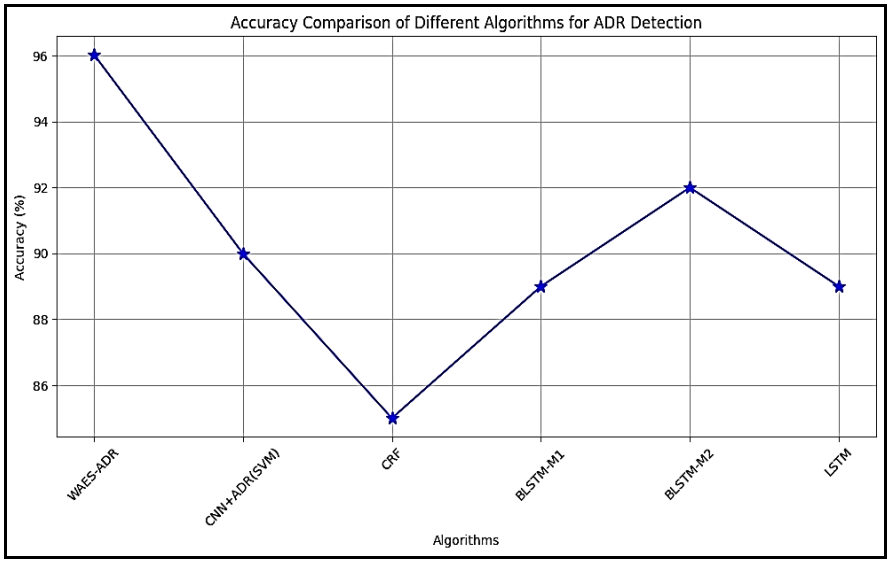

Figure 5. Accuracy Comparison of ADR Detection Algorithms

Receiver Operating Characteristic (ROC) statistic captured in Figure 6, which extends the findings in Figure 5. The graphical representation of the AUC may aid us in confirming certain characteristics of the algorithms in terms of the true positive rate (sensitivity) and false positive rate. Furthermore, the WAES-ADR model's distinctive curve shows how well it can distinguish between true positive and false positive ADR events.

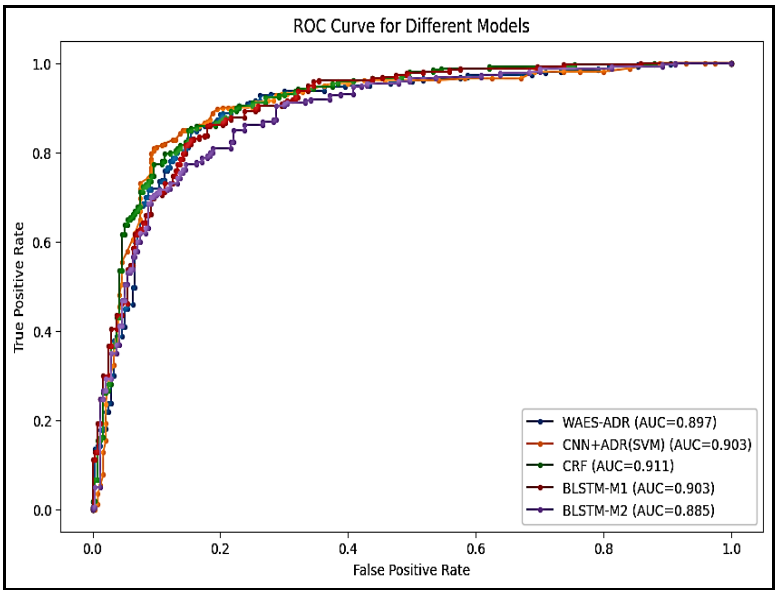

Figure 6. ROC Curve for ADR Detection Algorithms

5. CONCLUSION

This work talks about a novel approach that combines WAE autoencoders with algorithms for detecting adverse drug reactions in an attempt to improve drug recommendation systems and the safety of patients. Through exhaustive testing, we have shown that the patent of our approach makes it possible to develop individual pharmaceutical recommendations without adverse reactions. The findings demonstrate significant improvement in the accuracy of the recommendations as the 96.04 percentage rate recording was achieved. The integration of ADR detection systems has advanced the protection of the patients by making it possible to effectively anticipate possible adverse effects to prescription medicine. To moving forward, we have to put more work into our approach so that it's performance and scalability is improved for a smoother integration into real life health care systems. The integration of other data sources into medication recommendation systems, including genomic information or electronic health records, should accelerate the understanding of patient demographics and improve the quality of drug recommendations. Furthermore, there are countless opportunities to refine and enhance personalized medical methods thanks to the continuous development and expansion of deep learning and artificial intelligence technologies. We conclude that deep learning-powered drug recommendation systems and ADR detection techniques have the potential to transform healthcare delivery. Our study demonstrates this by championing patient-centered care and striving for better patient outcomes. Our research contributes to the ongoing evolution of precision medicine practices, paving the way for a future healthcare landscape marked by improved quality of care and patient well-being.

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J. Omana: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
P. N. Jeipratha: Project Administration, Writing – Review & Editing;
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CONFLICT OF INTERESTS

No conflicts of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

REFERENCES

[1] S. Dongre and J. Agrawal, "Deep-Learning-Based Drug Recommendation and ADR Detection Healthcare Model on Social Media," *In IEEE Transactions on Computational Social Systems*, vol. 10, no. 4, pp. 1791-1799, Aug 2023.

[2] N. Saxena, P. Saxena and S. Veenadhari, "Adaptive Multi-Hop Deep Learning based Drug Recommendation System with Selective Coverage Mechanism," *In 2023 IEEE 12th International Conference on Communication Systems and Network Technologies (CSNT)*, Bhopal, India, pp. 133-138, 2023.

[3] S. Garg, "Drug Recommendation System based on Sentiment Analysis of Drug Reviews using Machine Learning," *In 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, Noida, India, pp. 175-181, 2021, https://doi.org/10.1109/Confluence51648.2021.9377188.

[4] T. O. Omodunbi, G. E. Alilu and R. N. Ikono, "Drug Recommender Systems: A Review of State-of-the-Art Algorithms," *In 2022 5th Information Technology for Education and Development (ITED)*, Abuja, Nigeria, pp. 1-8, 2022, https://doi.org/10.1109/ITED56637.2022.10051591.

[5] A. Ghuribi, S. Mohammed and S. A. Mohd Noah. "A comprehensive overview of recommender system and sentiment analysis," *ArXiv*, pp. 1-36, 2021, https://doi.org/10.48550/arXiv.2109.08794.

[6] S. Haw, J. Jayapradha, E. Abdulwahab Anaam and H. A. Santoso, "Exploring Recommender Systems in the Healthcare: A Review on Methods, Applications and Evaluations," *International Journal on Robotics, Automation and Sciences*, vol. 6, no. 2, pp. 6-15, 2024.

[7] L. Yao, J. Zhong, X. Zhang and L. Luo, "Correlated Wasserstein Autoencoder for Implicit Data Recommendation," *In 2020 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, Melbourne, Australia, pp. 417-422, 2020, https://doi.org/10.1109/WIIAT50758.2020.00061.

[8] H. Liu, X. Gu, and D. Samaras, "Wasserstein GAN with quadratic transport cost," *In Proceedings of the IEEE/CVF international conference on computer vision*, pp. 4832-4841, 2019.

[9] A. A. Aljabr and K. Kumar, "Design and implementation of Internet of Medical Things (IoMT) using artificial intelligent for mobile-healthcare," Meas. Sensors, vol. 24, pp.1-12, Dec 2022.

[10] F. Godin, B. Vandersmissen, W. De Neve and R. Van de Walle, “Multimedia lab@ acl wnut ner shared task: Named entity recognition for twitter microposts using distributed word representations,” In Proceedings of the workshop on noisy user-generated text, pp. 146-153, July 2015.

[11] A. Nikfarjam, A. Sarker, K. O’connor, R. Ginn and G. Gonzalez, “Pharmacovigilance from social media: mining adverse drug reaction mentions using sequence labeling with word embedding cluster features,” Journal of the American Medical Informatics Association, vol. 22, no. 3, pp. 671-681, 2015, https://doi.org/10.1093/jamia/ocu041.

[12] A. Balahur and J. M. Perea-Ortega, "Sentiment analysis system adaptation for multilingual processing: The case of tweets," *Inf. Process. Manage.*, vol. 51, no. 4, pp. 547-556, July 2015, https://doi.org/10.1016/j.ipm.2014.10.004.

[13] Y. Wen, S. J. Kim, S. Avrillon, J. T. Levine, F. Hug and J. L. Pons, "A Deep CNN Framework for Neural Drive Estimation From HD-EMG Across Contraction Intensities and Joint Angles," In IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 2950-2959, 2022, https://doi.org/10.1109/TNSRE.2022.3215246.

[14] Y. Tong, Y. Luo, Z. Zhang, S. Sadiq and P. Cui, "Collaborative Generative Adversarial Network for Recommendation Systems," *In 2019 IEEE 35th International Conference on Data Engineering Workshops (ICDEW)*, Macao, China, pp. 161-168, 2019, https://doi.org/10.1109/ICDEW.2019.00-16.

[15] A. Graves and J. Schmidhuber, “Framewise phoneme classification with bidirectional LSTM and other neural network architectures,” *Neural Networks*, vol. 18, no. 5-6, pp. 602-610, 2005, https://doi.org/10.1016/j.neunet.2005.06.042.

[16] M. Fetanat, M. Stevens, P. Jain, C. Hayward, E. Meijering and N. H. Lovell, "Fully Elman Neural Network: A Novel Deep Recurrent Neural Network Optimized by an Improved Harris Hawks Algorithm for Classification of Pulmonary Arterial Wedge Pressure," *In IEEE Transactions on Biomedical Engineering*, vol. 69, no. 5, pp. 1733-1744, May 2022, https://doi.org/10.1109/TBME.2021.3129459 .

[17] J. Jayapradha, Y. Kulkarni, L. Vadhanie, P. Naveen and E. Abdulwahab Anaam. “Treatment Recommendation using BERT Personalization,” Journal of Informatics and Web Engineering, vol. 3, no. 3, 2024, pp. 41-62, https://doi.org/10.33093/jiwe.2024.3.3.3.

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