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Research Article

Federated Learning Based Model for Recommendation System Based in Health Care

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ABSTRACT

Precision Medicine is an emerging healthcare approach that focuses on tailoring treatments for individual patients. The implementation of patient-centred Decision Support Systems, including Health Recommender Systems, is a key component of this initiative, aimed at augmenting the accuracy and individualization of healthcare delivery. However, a significant challenge in developing these systems is the confidential nature of the medical data, as these systems require large volumes of data to function effectively. Unfortunately, medical data are distributed across multiple institutions and cannot be centralized due to privacy concerns. To overcome this challenge, this position paper presents an architecture that uses Federated Learning to build a HRS (Health Recommender System). Federated Learning enables the use of data from different institutions without requiring direct data sharing. To demonstrate the feasibility of this approach, we developed a Federated Drug Recommendation System designed to assist physicians in prescribing medications by utilizing historical data on disease-drug interactions and pharmaceutical information. As this is a position paper, we focus on presenting a proof-of-concept utilizing publicly available, non-sensitive datasets.

Keywords: Federated learning, Health Care, Recommendation, Decision support.

INTRODUCTION

With the rapid advancements in perception and computing technologies, machine learning is progressively being used to assist doctors in diagnosing diseases and performing medical procedures. Many methods are being proposed to monitor individuals' health and diagnose diseases, often achieving performance that rivals or even exceeds that of human doctors, especially in the field of medical imaging. Furthermore, machine learning enables early disease detection through the monitoring of daily behaviors using simple wearable sensors. For example, changes in gait or finger flexibility serve as early indicators of cognitive diseases like Parkinson's disease [1][2]. Some studies also focus on improving personalization in healthcare. However, a significant problem for successful healthcare applications is the need for huge amounts of categorized data. In reality, such data is often fragmented and individuals or organizations are reluctant to share their private information. Furthermore, stringent regulations are in place to prevent data leaks, which results in data being isolated across different clients and creating data "islands." This makes it difficult to build effective machine learning models using aggregated data [3][4]. In this situation, FL (federated learning) emerges as a solution to build powerful machine learning models while ensuring data privacy. Federated learning enables the aggregation of information from multiple clients without exchanging sensitive data, thus safeguarding privacy and security. The concept is first introduced by Google, which proposes the FedAvg algorithm to train machine learning models by aggregating data from distributed mobile devices without direct data exchange. The main idea behind this method is to replace direct data sharing with exchanges of model parameters, which helps address the problem of data isolation. While federated learning is still an emerging field, it garners significant

attention [5][6]. Federated learning, based on data characteristics, is classified into three primary categories: horizontal, vertical, and transfer. The horizontal approach to federated learning is employed when multiple clients possess datasets with similar features but divergent data samples. In this context, the data undergoes horizontal partitioning, signifying that although clients share an identical feature space, they maintain separate and distinct user records.

FL can be specifically applied in the following situations:

Non-IID data: The classic machine learning is based on the hypothesis that that data is independently and identically distributed (IID). However, this hypothesis often does not hold true in practical scenarios [7][8]. Each client tends to have distinct behaviours. As a result, the data collected from one client may be biased and differ significantly from that of others. This leads to the presence of non-IID or heterogeneous data, which can create challenges for machine learning models.

Unbalanced data distribution: An unbalanced data distribution arises when some participants in the training dataset have a disproportionate share of relevant data. For instance, in a training scenario involving both hospitals and individuals, hospitals are likely to contribute much larger sample sizes compared to individuals. Moreover, data related to the same disease can differ significantly between hospitals due to variations in equipment, staff, and other factors. These disparities can make it challenging for machine learning models to generalize effectively to new and diverse datasets.

Data privacy protection: The advent of stringent data privacy laws, especially in the healthcare domain, has significantly restricted the ability to collect large datasets for model training [9][10]. Clinical data often includes sensitive patient information, requiring strict limitations on data access and permitting only the use of model parameters. This presents a major challenge for machine learning models, which rely on extensive and diverse datasets to accurately identify patterns and make reliable predictions.

Personalization plays an important role in healthcare applications because individuals, hospitals, and countries often differ in demographics, lifestyles, and other health-related factors, creating a challenge known as the non-iid (non-identically and independently distributed) issue. As a result, the focus shifts toward achieving better personalized healthcare by developing FL (federated learning) models tailored to each client. These models preserve the unique information of each client while leveraging their commonalities. For example, as shown in Fig. 1, three different clients A, B, and C have distinct data distribution statistics. Client A (an adult) and client B (a child) exhibit different lifestyles and activity patterns [11][12]. Although federated learning functions in a standard manner, it struggles to address the non-iid issue effectively. This limitation significantly impacts the performance of existing federated learning algorithms.

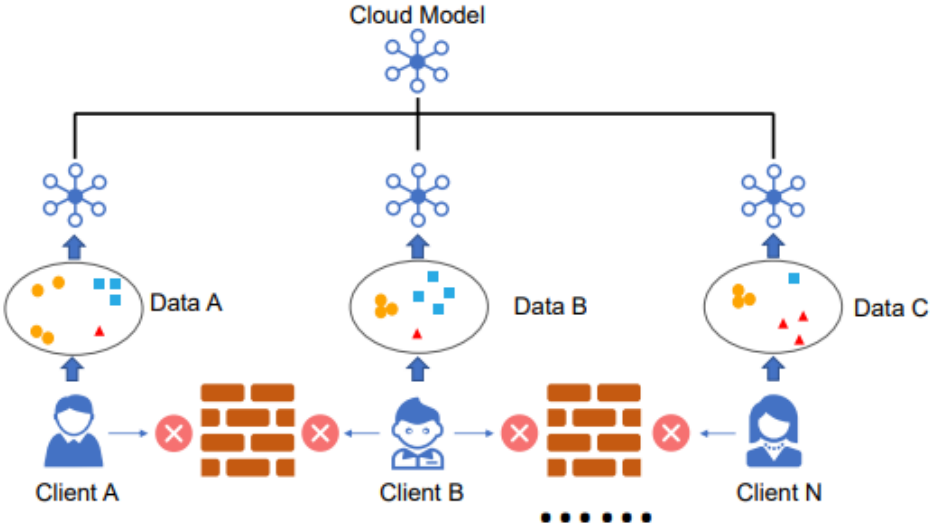

Fig. 1. In federated learning, non-IID data refer to instances in which each client possesses data with distinct distributions.

Personalized federated learning integrates the advantages of both personalized models and federated learning, while considering the different properties and preferences of each client. Its methodology typically includes five main approaches: parameter decoupling, knowledge distillation, multitask learning, model interpolation and clustering.

In the parameter decoupling approach, the model parameters are divided into two categories: base parameters and personalized parameters. Base parameters are shared between the client and the server, while personalized parameters remain stored privately on the client side. The knowledge distillation approach transfers knowledge from a teacher model to a student model, which significantly improves the performance of local models [13][14]. The multitask learning method views each client's model as a different task and frames the learning process of personalized federated models as a multi-task learning problem. The model interpolation approach simultaneously learns a global model for all clients and a local model for each individual client. It typically balances between the global and local models to achieve optimal personalization. The clustering method focuses on creating similar personalized models for clients with similar data distributions. Existing methods in this branch either treat model learning and client clustering as separate tasks or base model learning on prior assumptions about clustering such as selecting the number of clusters or choosing a specific clustering method. In contrast, methods that focus on learning personalized models implicitly discover clustering structures among clients. These methods do not rely on prior assumptions about clustering, leading to better performance through improved adaptation to local data. Among these methods, the most relevant approaches are divided into two groups: personalized models based on similarity and personalized models using a mixture of components [15][16]. The first group includes methods like FPFC, FedAMP, L2GD, FedRoD, and SuPerFed, among others. These approaches generate personalized models by leveraging specific similarity network topologies of clients' local data, such as complete graphs and star graphs. However, such topologies limit their applicability in medical scenarios. For instance, FPFC and FedAMP rely on complete graphs to create personalized models, while L2GD, FedRoD, and SuPerFed use star graphs for the same purpose.

LITERATURE REVIEW

S. Puppala, et al. (2024) introduced a groundbreaking method to healthcare information retrieval and engagement through a personalized chatbot, powered by Federated Learning-based GPT [17]. It was designed to seamlessly aggregate and curate diverse healthcare data sources including research papers, multimedia resources and news articles. By using Federated Learning techniques, the GPT model was trained on distributed data sources, certifying confidentiality and security while delivering personalized insights and recommendations. Users interacted with the chatbot via an intuitive interface, gaining access to tailored information and real-time updates on medical research and news. The system's innovative architecture enabled efficient processing of input files, parsing and enriching text data with metadata and generating relevant questions and answers using advanced language models. Through facilitating interactive access to a wealth of healthcare information, this personalized chatbot system represented a significant advancement in healthcare communication and knowledge dissemination.

S. T. Ahmed, et al. (2024) discussed a new TinyML-based model for resource allocation and sharing in medical consumer devices [18]. The proposed framework was developed using FL (Federated Learning) models to extract resource utilization patterns at the individual user level. These locally computed models were further supported by an edge computation layer, which helped locate the extraction of resource patterns. The technique was deployed on a dynamic server-based resource pooling system, allowing effective analysis and resource scheduling. It was also expanded to develop a reliable recommendation model for medical resource management. The framework trained 128 clusters, consisting of 6,400 rural and 12,800 urban IoT device samples, for resource allocation and scheduling using the telemedicine protocol (TelMED). This method achieved an efficiency of 93.21% for urban user recommendations and 94.72% for rural users.

M. Guduri, et al. (2024) presented a blockchain-based lightweight encryption strategy combined with federated learning to solve the scalability and trust concerns surrounding EHR (electronic health records). After implementing lightweight encryption, the EHR data was stored in a decentralized cloud system [19]. The study emphasized the importance of protecting the privacy and security of distant patients' health records. With stakeholders now having access to a secure portal and cloud data being inaccessible, the likelihood of attacks on electronic healthcare records was expected to decrease. The study ensured full encryption throughout the entire communication process using federated learning. Without the need for a reliable 3rd party, the system set up active smart contracts at runtime between the sensor and the data user to facilitate the transfer of EHR data. To maintain data privacy between the owner and the user during the contract's execution, the system employed a highly effective proxy re-encryption mechanism, supported by federated learning. It was observed that the PSNR (Peak Signal-to-Noise Ratio) and Mean Squared Error (MSE) of the proposed model were 39 (1.07×) and 229.6 (1.02×), respectively.

In 2024, F. Hu and colleagues introduced an improved consensus mechanism for selecting master nodes, with the objective of identifying and mitigating dishonest actions to enhance the reliability and integrity of collaborative model

training [20]. They also investigated and developed healthcare and medical data collaboration services for real-world application. To evaluate the efficacy of the FL-HMChain, they implemented a Federated Learning model based on Convolutional Neural Networks (FL-CNN-HMChain) for medical image recognition. This model demonstrated superior performance compared to the standard CNN, achieving a 4.7% higher Area Under the Curve (AUC) and 7% increase in accuracy (ACC). Furthermore, the integration of a blockchain-based parameter transfer system in federated learning facilitates secure parameter exchange between local and global models, thereby significantly reducing the risk of privacy breaches.

In 2023, G. Shen and colleagues introduced an effective and privacy-preserving online diagnosis framework for e-healthcare systems utilizing a Federated Learning Mechanism (FLM) [21]. This approach reformulated the challenge of data sharing among data owners as a machine learning task by facilitating the exchange of local model parameters instead of raw data, thereby safeguarding the privacy of the training datasets. The system integrated a homomorphic encryption scheme with the Support Vector Machine (SVM) algorithm to classify patients' physiological data securely and effectively. Furthermore, a novel technique was developed to reconstruct the SVM decision function, mitigating potential exposure of model parameters. Security evaluations corroborated that the proposed framework effectively maintained data privacy under specified threat conditions, and experimental results demonstrated its high efficiency.

B. Wang, et al. (2023) presented a PPFLHE (privacy-preserving federated learning scheme with homomorphic encryption) [22]. Specifically, on the client side, homomorphic encryption technology was used to encrypt the training models shared by users, ensuring both security and privacy. Furthermore, to prevent internal attacks, AC (Access Control) technology was employed to verify the user's identity and determine whether they were trusted. On the server side, an Acknowledgment (ACK) mechanism was developed to temporarily remove dropped or unresponsive users, reducing waiting delays and communication overhead, while solving the problem of users exiting during training. Theoretical analysis and experimental results showed that the proposed scheme achieved high data utility and classification accuracy (81.53%), along with low communication delay, all while preserving privacy, compared to state-of-the-art methods.

In 2023, M. Nasimuzzaman and colleagues proposed a framework for evaluating the security of e-healthcare systems by integrating pre-processed deep learning models with federated learning [23]. The healthcare industry is increasingly implementing infrastructure support for e-healthcare services. This approach aimed to establish a secure platform that protected both patients and medical professionals, with the potential to supersede existing healthcare systems. Despite its increasing adoption, several data security challenges remain unresolved. The study employed a classification-based methodology utilizing CNN and MLP architectures, incorporating pre-trained feature extractors, such as ResNet-50, VGG16, and Inception-v3.

In 2022, M. Akter and colleagues introduced a privacy-preserving framework termed the Federated Edge Aggregator, or Edge Intelligence, designed to safeguard Smart Healthcare Systems at the edge from privacy threats utilizing federated learning [24]. This framework incorporates an iterative Convolutional Neural Network (CNN) model with artificial noise functions to maintain the equilibrium between data privacy and model accuracy. Furthermore, the study presented a theoretical convergence bound for the loss function of the federated learning model within the Edge Intelligence. The framework was evaluated against contemporary methods using widely recognized datasets, including MNIST, CIFAR10, STL10, and COVID-19 chest X-rays. The experimental results demonstrated that the proposed model achieved 90% accuracy and a robust privacy guarantee, surpassing the baseline performance approaches.

In 2021, H. Elayan et al. introduced a Deep Federated Learning approach designed for distributed healthcare systems with a focus on preserving user privacy within a distributed framework [25]. In addition, they developed an algorithm to automate the collection of the training data. To address the challenge of imperfect healthcare data for deep learning models, researchers have conducted experiments utilizing deep federated learning in conjunction with Transfer Learning for skin disease detection. The results demonstrated that federated learning enhanced the Area Under the Curve (AUC) of the centralized model, achieving a score of 0.97. The framework also maintained high performance across federated rounds, exhibiting high accuracy, precision, recall, and F1-score. Although the federated learning system marginally affected service quality, particularly regarding model conversion time, it successfully supported decentralized model training, while safeguarding user privacy.

RESEARCH METHODOLOGY

The presented F-HRS framework consists of three key elements: the input data, the recommendation algorithm and the Federated technique. This section thoroughly describes each of these elements. Figure 2 provides an architectural representation of how these elements are combined. The subsequent parts further clarify this diagram.

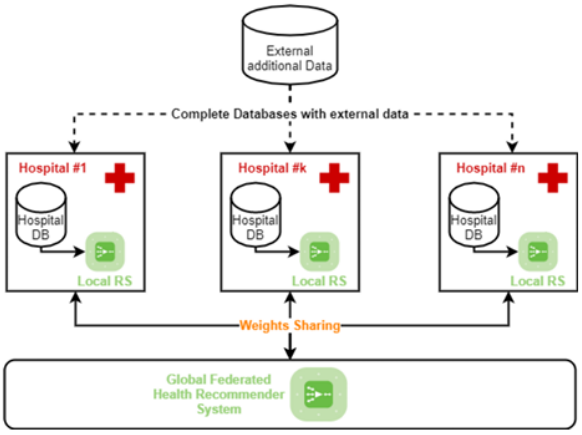

Figure 2: F-HRS Architecture.

3.1 Input Data

As illustrated in figure 2, F-HRS leverages multiple sorts of databases. On one side, the system utilizes hospital-specific data, including patients' medical histories, profiles, and examination results. These records are stored within individual hospital databases and remain inaccessible to others due to privacy restrictions. Conversely, the system also integrates an external database that contains information on recommendation matters. Different from the hospital databases, this external database is freely available, allowing it to be accessed and utilized by various hospitals.

3.2 Recommendation Algorithm

F-HRS uses Neural Collaborative Filtering (NCF) as recommendation algorithm. This algorithm operates on the collaborative filtering principal. This approach, widely recognized in recommendation systems, identifies users with preferences similar to the target user and suggests items favoured or used by those alike users. This algorithm is chosen for its ability to integrate a neural network into the Collaborative Filtering approach. The neural network enables the system to automatically learn the interaction function between users and items. Unlike the baseline algorithmic solution, this process does not require manual intervention. Instead, it leverages data to refine recommendations autonomously. Additionally, the NCF Algorithm facilitates the seamless inclusion of content features representing users and/or items, resulting in more precise and appropriate recommendations.

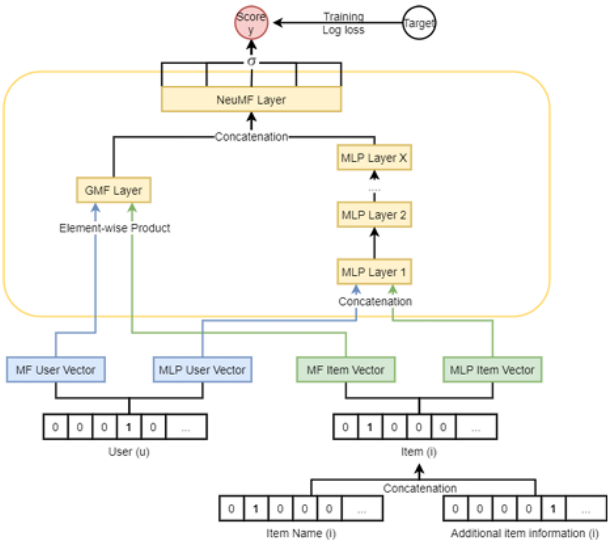

Figure 3: Neural Collaborative Filtering Architecture.

Figure 3 illustrates the Neural Collaborative Filtering (NCF) algorithm, which functions by utilizing both positive and negative user-item interaction examples as inputs. For each user or patient, four negative examples were generated by selecting items with which they did not interact. These interactions are organized into a binary matrix, which can be further enhanced by incorporating binary vectors for the items, as shown in Figure 3. The user and item vectors in this matrix are transformed into d-dimensional representations that are typically set to eight dimensions by default. These combined vectors are subsequently input into a neural network, traversing multiple hidden layers of a deep neural network to capture complex user-item relationships. A typical NCF model comprises to 4-5 fully connected layers, each containing fewer than 100 neurons. The final layer employs a sigmoid activation function to produce an output between zero and one, representing the probability of interaction between a user and an item. The algorithm is generally trained over five epochs with a new set of negative samples generated for each user in every epoch.

3.3 Federated Learning

Following steps are implemented to integrate the Federated approach into the HRS:

1. Initialization: The global model is initialized, either randomly or through pre-training with open-source data. This work conducts tests using a common practice in federated learning named random weight initialization.

2. Client Selection: Participating entities (e.g., hospitals) are chosen to contribute to the federated training. By default, this architecture chooses clients (e.g., hospital servers) in the order they initiate, without considering the exclusion of any participants. However, if needed, the framework can be extended to include features for client selection according to a specific principle, such as efficiency or quality of dataset.

3. Distribution: The global model's weights are distributed to the participating entities. This step is crucial and requires employing the most effective method for distributing weights securely. Techniques such as homomorphic encryption (HE), classical encryption (e.g., TLS), differential privacy (DP), or Secure Multi-party Computation (SMPC) can be utilized to ensure security.

4. Update and Upload: Each participating entity (e.g., hospital) uses its local data for the model training (e.g., Collaborative Filtering Algorithm) and then uploads the revised model weights to the server.

5. Aggregation: The gathered weights are combined, and the global model is updated with the result. Various aggregation techniques can be used, such as a weighted sum, depending on the data type. The presented framework applies the Federated Averaging technique. The use of this technique is quite common due to its use of ease and efficiency. Federated Averaging computes the global model's weights by averaging the weights of the client models.

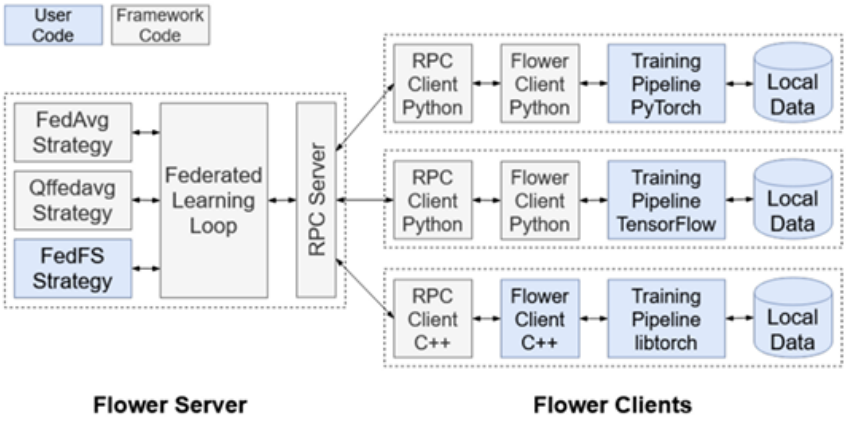

Figure 4: Flower core framework architecture

Each step, other than Initialization, is repeated until the global model obtains the required efficiency level. A number of architectures are present for implementing the Federated technique. For this project, Flower is selected. Flower is a freely accessible system that helps the implementation of machine learning algorithms in federated settings. Figure 3 shows its framework, which includes an aggregation server and multiple clients operating in various settings. As opposed to other Federated Learning architectures, the key distinction of Flower is its facilitation for a broad range of machine learning back-end libraries (i.e., Pytorch, TensorFlow, and Jax) due to its ML model-agnostic design. Flower is adaptable too, supporting both single-host simulations and federated deployments across multiple hosts.

RESULT AND DISCUSSION

This study focuses on healthcare recommendations. The federated learning is applied for the which will improve results of the collaborative filtering. The proposed algorithm is implemented on the public dataset and results are generated in the form of recommendations. The results of the projected model are also compared with existing models in terms of certain parameters

4.1. Parameters Explanation

In this section performance analysis metric are presented. The details of the metrics are presented below: -

- Accuracy: - Accuracy assesses the efficacy of data recovery and processing in the evidence domain. It represents the proportion of correctly classified results and is calculated using the following formula:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

- Precision: - Precision is a metric used to evaluate the performance by calculating the proportion of correctly predicted positive instances among all instances predicted as positive. This can be expressed using the following formula:

$$Precision = \frac{TP}{TP + FP}$$

- Recall: - The Recall, also referred to as sensitivity, quantifies the proportion of correctly identified positive instances among all the actual positive instances. It was computed using the following formula:

$$Recall = \frac{TP}{TP + FN}$$

4.2. Results

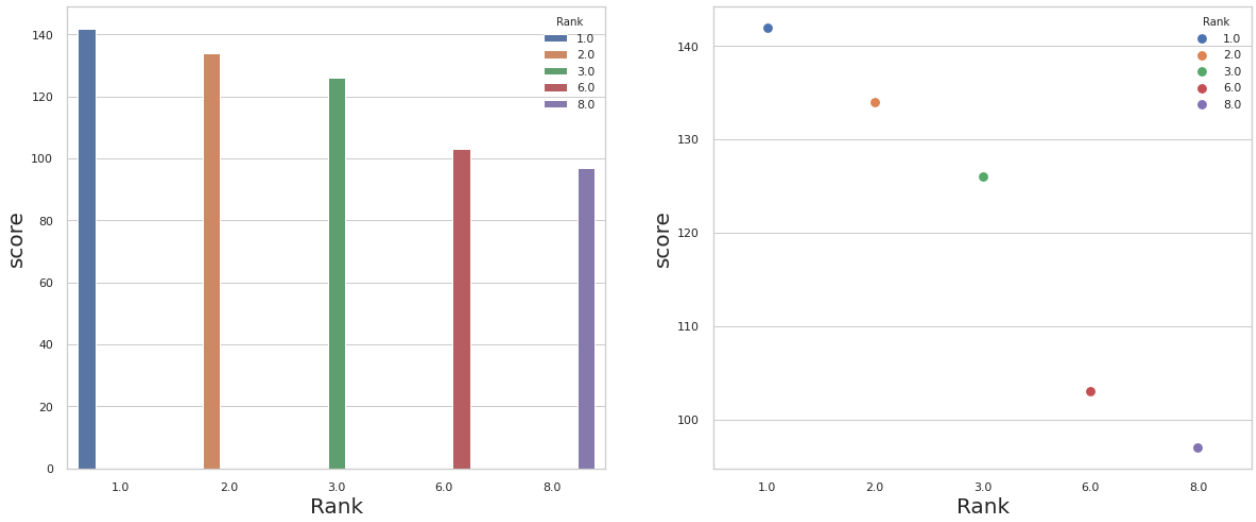

Figure 5: Group Recommendation with three User

As shown in figure, groups are formed with three users in each group. The Score of each group is plotted correspond to rank. The x axis values show the rank value and y axis shows the score value of the group recommendations.

Table 1: Performance Analysis

Model	Accuracy	Precision	Recall
COM Model	89.90 percent	89 percent	89 percent
Deep Learning Model	90.12 percent	90 percent	90 percent
Multi attention model	92.34 percent	92 percent	92 percent
Proposed Model	95.67 percent	96 percent	96 percent

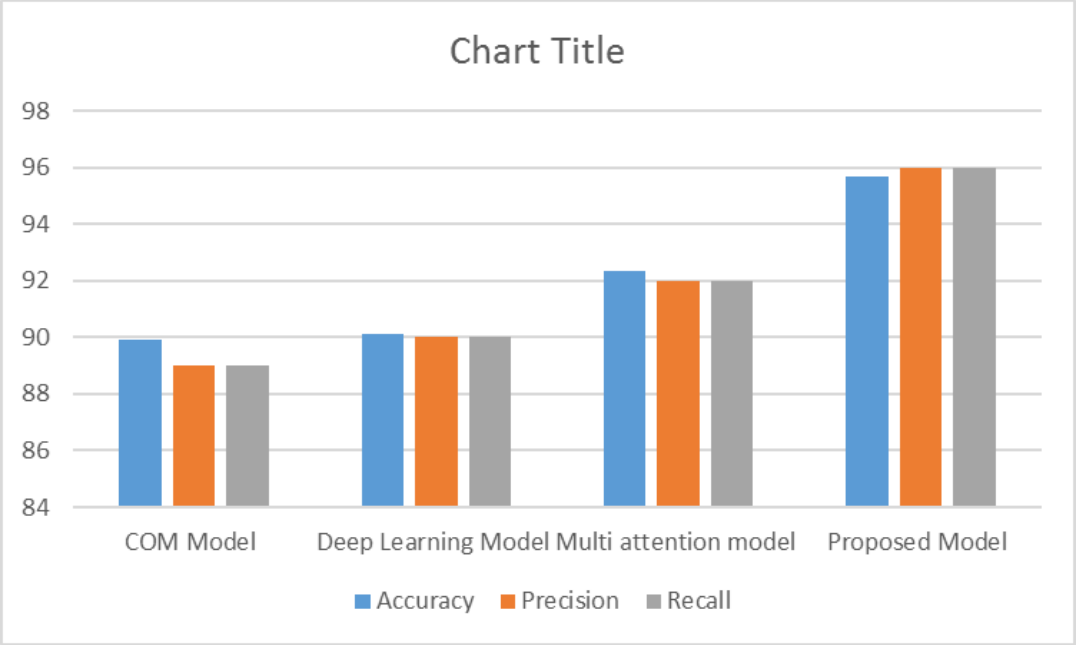

Figure 6: Performance Analysis

As shown in figure 6, the performance of projected model is compared with existing models for the group recommendations. It is analysed that projected model achieves accuracy of 95 % which is approx. 3 % higher than existing models.

CONCLUSION

This study introduces the utilization of Federated Learning to develop a health recommendation model, addressing the challenge of limited data accessibility encountered by medical institutions when constructing patient-centered decision support systems. By employing federated learning, the model can be trained on data from diverse institutions without exchanging raw data, thereby resulting in a more generalizable and robust recommendation system. This study validated the feasibility of this methodology by utilizing open-source datasets to develop a drug recommendation system. The proposed federated learning approach not only enhances data privacy and security, but also enables collaborative learning across multiple healthcare providers, potentially improving the accuracy and reliability of health recommendations.

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