Neutrosophic Sets and Systems, Vol. 66, 2024
University of New Mexico

Neutrosophic Cognitive Maps for Clinical Decision Making in Mental Healthcare: A Federated Learning Approach

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Abstract: Due to data privacy concerns and a lack of broadly applicable modelling approaches, mental health prediction encounters substantial challenges. This research introduces a pioneering decentralized framework integrating federated learning with Neutrosophic Cognitive Maps (NCMs) to facilitate secure and accurate mental health predictions while preserving data privacy. This innovative approach allows collaborative NCMs training on sensitive patient data across diverse sites without centralizing or transferring the data. The NCMs incorporated into the framework effectively model relationships between various symptoms and mental health states, offering interpretable insights into the complex dynamics of mental health. To address the limitations of local data availability, a multi-task learning methodology is employed, leveraging commonalities between related mental health prediction tasks to enhance modelling. Experiments are done on a synthetic mental health dataset to validate the proposed approach, demonstrating significant improvements. The decentralized nature of the approach ensures robust privacy guarantees by preventing direct access to patient data. The proposed framework contributes to the responsible application of soft computing and AI in the sensitive mental health domain. Furthermore, the interpretability of NCM models facilitates a nuanced analysis of indeterminate interrelationships between various psychological concepts, offering valuable support for data-driven decision-making in mental health contexts.

Keywords: Federated Learning; Neutrosophic Cognitive Maps (NCMs); Mental Health; Psychological Concepts; SDG 3-4;

1. Introduction

Mental health, a critical aspect of overall well-being, requires innovative data analysis and modelling approaches. Traditional methodologies in mental health modelling face significant challenges, particularly when it comes to protecting individual privacy and accurately representing the inherent uncertainty associated with mental health data. This paper explores a pioneering integration of two powerful paradigms, federated learning and Neutrosophic Cognitive Maps (NCMs), to improve the diagnostic results or prediction to handle indeterminacy-related challenges. The rise of digital health records and the growing adoption of mobile mental health apps have created vast datasets. However, using these datasets for meaningful insights raises ethical concerns about the privacy of sensitive information.

Federated learning, a decentralized machine learning approach, represents a promising solution [1]. By enabling modelling across distributed devices without exposing raw data, federated learning ensures the confidentiality of individual records, making it particularly suitable for the sensitive nature of mental health data. At the same time, mental health data often exhibit inherent uncertainty and inaccuracy. NCMs, an extension of traditional cognitive maps, represent a new way of dealing with uncertainty by incorporating neutrosophic logic [2]. This logic accepts indeterminate and inconsistent information and provides a robust framework for modelling the complexity of mental health processes.

By decentralizing the model training process, federated learning addresses privacy concerns, while NCMs improve the representation of uncertainty and imprecision within cognitive modelling. This research work aims to explore these concepts with the overarching goal of advancing mental health modelling methodology. At a time when mental health is an escalating global issue, this research seeks to contribute to a more ethical, efficient and privacy-friendly approach to mental health data analysis and modelling.

The primary objective of this research is to develop and evaluate federated learning approaches that leverage NCMs to enhance healthcare decision support while ensuring the privacy and security of sensitive patient data.

This research addresses the following objectives:

1. To design a federated learning framework that accommodates NCMs and their associated uncertainty, indeterminacy, and partial truth.
2. Integrating NCMs into the federated learning process to model and reason with complex medical data, capturing indeterminate and contradictory information nuances.
3. To develop optimizations and personalization techniques for efficient federated learning of NCMs across heterogeneous medical datasets.
4. To evaluate the feasibility and performance of the proposed federated-NCMs approach using simulations on synthetic medical datasets.
5. To analyze the reasoning capability of the proposed federated-NCMs method.

The paper unfolds in a structured manner, beginning with an introduction that outlines the background and motivation. A comprehensive literature review builds the foundation by examining models of federated learning and NCMs. The theoretical framework represents the principles underlying federated learning and NCMs.

The methodology details the research design, data collection, and implementation of an integrated model. Model development and integration are explored in section three, which provides an overview of the architecture, training processes, and challenges encountered. The results and discussion show the integrated model's performance, compare it with existing approaches, and discuss implications. Practical applications and use cases in mental health scenarios highlight the potential benefits for clinicians, researchers, and patients.

The paper concludes with a comprehensive summary of key findings, contributions, and recommendations for future research. This research contributes to the ongoing discourse on privacy-preserving mental health modelling and provides a promising framework combining federated learning and NCMs.

2. Literature Survey

A survey by Liang et al. [1] offers a comprehensive overview of federated learning techniques in intelligent healthcare. Despite introducing various federated learning algorithms, the paper needs a detailed comparison of their performance and effectiveness in smart healthcare scenarios. The survey contributes to understanding the environment of federated learning applications in healthcare but does not provide insight into the specific nuances and requirements of intelligent healthcare environments. Tedeshini et al. [3] focused on decentralized, federated learning for tumour segmentation. Using methodologies such as FedAvg, FedClus, and FedVote, the study explores their applicability in the context of tumour segmentation. However, the study could be more extensive, especially the specific application of tumour segmentation. It must address broader applications requiring different or more complex models, such as tumour detection, classification or prediction. Gram et al. [4] contributed to this field by implementing and evaluating robust aggregation methods in federated learning for healthcare.

Fuzzy theory was introduced in 1985 by Lofti A. Zadeh [5]. Since then, fuzzy theory has found many real-world applications. Fuzzy sets have been extended and generalized into intuitionistic fuzzy sets (IFS) and neutrosophic sets. Fuzzy Cognitive Maps (FCMs) [6] are graphical models representing the relationships and interactions between different variables within a system. Integrating FCMs into medical decision-making processes has emerged as a remarkable research area that can improve understanding of complex systems characterized by uncertainty. Research by Jayashree et al. [7] applied FCMs for geospatial risk prediction of dengue outbreaks. These studies demonstrate FCM's utility in capturing complex medical decision dynamics. Beyond dengue applications, Evangelia et al. developed time-dependent FCMs to represent the temporal evolution of medical conditions for improved diagnostics. Greeda et al. [8] presented a survey on FCM techniques used in medicine, encompassing disease diagnosis, treatment planning, and medical imaging.

FCMs techniques enhance complex diagnosis under uncertainty by representing the multifaceted relationships between variables affecting disease diagnosis and management. In healthcare, federated learning is paramount for the privacy and security of patient data. Federated learning enables training a collaborative model across decentralized entities without centralizing raw data, ensuring that sensitive medical data remains localized. Integrating FCM and federated learning is valuable in addressing complex medical decision-making processes was studied by Hoyos et al. [9-12]. However, Hoyos et al.'s study falls short of providing a comprehensive assessment of uncertainty and indeterminacy that is inherent in mental health diseases.

Neutrosophy is a branch of philosophy investigating neutralities' origin, nature, and scope and their interactions. Florentin Smarandache introduced neutrosophy in the 1990s [13]. Neutrosophy regards a proposition, hypothesis, concept, event, or entity depending on the modelling. Neutrosophy is the basis of the neutrosophic set, logic, probability, and statistics. Indeterminacy "I" is a concept in neutrosophy that measures the degree of neutrality or uncertainty of a proposition, event, theory, entity or concept. Neutrosophic Cognitive Maps (NCMs) are an extension of FCMs that can handle indeterminate relationships between two concepts, obtaining more significant sensitive results. It was introduced in [14] and has since been used to analyze diverse social issues [15-29]. NCMs have been modelled considerably on the AI focus to mimic the thinking-human approach. Here, it is unsupervised data and has a limited set of features.

Indeterminacy deals with imprecise and incomplete concepts characterized by unknown or neutral elements. A study by Ramalingam et al. [21] demonstrates the superiority of NCMs over FCMs in various scenarios, highlighting their greater accuracy and reliability. This becomes especially important in medical diagnostics, where uncertainties and incomplete information are inherent. The ability of NCM to represent unknown or neutral elements provides a unique advantage, especially when dealing with concepts or relationships where information is missing or uncertain. Zafar et al. [24] propose a mathematical model based on NCMs to analyze uncertain factors' role in spreading pandemics such as COVID-19.

3. Federated Learning using NCM

This paper proposes a novel methodology that synergistically combines federated learning with Neutrosophic Cognitive Maps (NCMs) to enable secure, privacy-preserving artificial intelligence for complex healthcare applications. The proposed approach aligns with the critical need for collaborative and ethical AI solutions in healthcare. The methodology's core is a decentralized, federated learning framework that facilitates model training on sensitive patient data distributed across multiple sites without requiring central data aggregation. This allows collaborative learning on NCMs while ensuring data privacy and security. The adaptive modelling capabilities of NCMs further allow for the capture of dynamic relationships between various medical concepts.

While this paper demonstrates the potential applicability of NCM in intelligent healthcare and decision-making, it does not validate the model with actual data or empirical evidence. Relying on hypothetical values and weights for concepts and associations in the NCM raises concerns about the actual dynamics and accuracy of the proposed model in depicting scenarios. Specific goals include creating privacy-preserving NCM models, formulating guidelines for federated training of NCMs, and evaluating the approach on real-world medical datasets.

3.1 Proposed System:

The proposed system's architecture as given in Figure 1 is the backbone of our innovative approach, seamlessly integrating components to enable federated learning with NCMs in mental health. This section provides detailed insight into the structural design, addressing limitations in existing systems and proposing a novel framework.

Before delving into the proposed architecture, it is essential to acknowledge the limitations of current systems. Existing models may struggle with the intricacies of mental health data, including heterogeneity, privacy concerns, and the dynamic nature of mental health conditions. These limitations set the stage for the innovative solutions proposed in the subsequent sections.

Our proposed system introduces a sophisticated architecture designed to overcome the identified limitations. It embraces a decentralized approach, ensuring enhanced data privacy, personalization, and effective learning.

The system comprises the following key components:

Heterogeneous data collector: The heterogeneous data collector is the entry point, adept at gathering diverse data types such as text, images, audio, and sensor readings. Its versatility allows for a comprehensive collection of heterogeneous mental health data from various sources.

Data handler: Upon data collection, the data handler takes charge of preprocessing tasks, including cleaning, normalization, and feature extraction. This ensures that the data is optimized for subsequent model training, addressing the challenges posed by the heterogeneity of mental health data.

Local database: The local database acts as a central repository, storing processed data for easy access during training. This organized storage facilitates efficient sampling for model training and promotes collaboration among decentralized components.

Multi-Tasker model trainer: At the heart of the proposed system, the multi-tasker model trainer facilitates simultaneous training for multiple mental health tasks. This component optimizes shared representations across tasks, leveraging collective knowledge to enhance overall model performance.

Algorithm refitter: The algorithm refitter complements the training process by fine-tuning models based on task-specific feedback. This ensures continuous improvement in model parameters, adapting to the dynamic nature of mental health conditions.

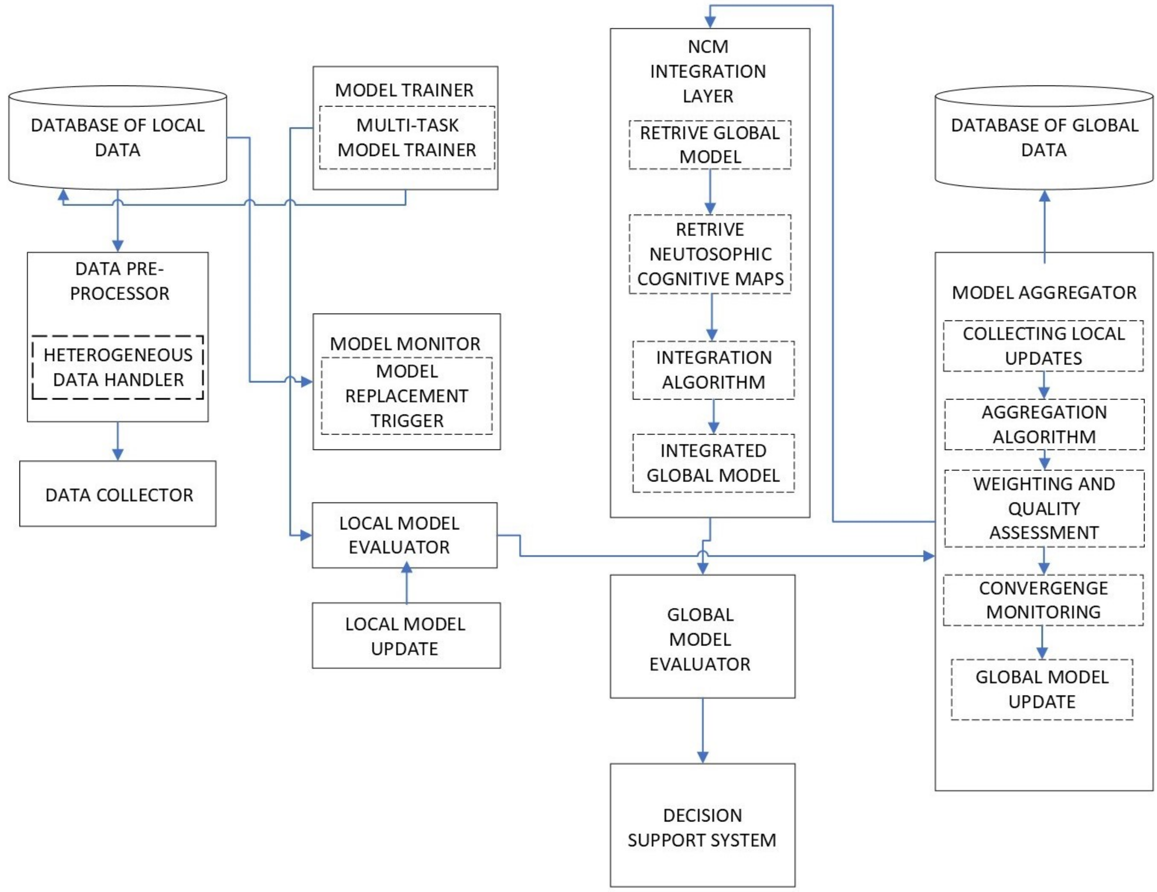

Figure 1. Architecture of the proposed system

Evaluator model: Post-training, the evaluator model assesses the performance of trained models, scoring them on relevant metrics. This critical evaluation provides insights into the effectiveness of the models, guiding further refinements.

Local model update: Each local database has its own local NCM model, which is updated iteratively during training. This decentralized approach allows specialization in understanding specific mental health conditions, improving model accuracy.

Model Aggregator: The local model updates are aggregated and used to update the global model; they are assessed by an expert for quality before the global model is updated.

The proposed system has several advantages: Adopting a federated learning approach prioritizes data privacy, allowing decentralized entities to contribute without compromising sensitive information. The system is designed to adapt and personalize models for various mental health tasks, ensuring tailored diagnoses for diverse conditions. Leveraging shared knowledge across tasks enhances the overall learning efficiency of the system, leading to improved mental health predictions. This proposed system addresses the unique challenges in mental health data analysis, offering a decentralized, privacy-preserving, and efficient solution. Indeterminate and uncertain relationship among the symptoms is handled correctly by the proposed algorithm.

Integrating federated learning and NCMs forms the core of our approach to addressing the complexity of mental health data analysis. Federated learning, with its focus on a collaborative training model and privacy protection, aligns seamlessly with the nuanced representation of uncertainty provided by NCM. On the other hand, because they explicitly reflect unknown or uncertain variables, NCMs excel at modelling the dynamic and complicated nature of mental health disorders. Combining these two methods provides a comprehensive solution that improves the accuracy and adaptability of mental health models while upholding strict privacy standards. By providing a more thorough understanding of intricate relationships and patterns, local models outfitted with NCMs provide the global model with distinctive insights into the dynamic nature of mental health disorders. NCMs' adaptive learning characteristics, which record changes over time, work in combination with FL's decentralized adaptive learning capabilities to guarantee that the model adapts dynamically to each person's unique mental health condition.

Moreover, NCMs' capacity to clearly describe uncertainties complements the ethical issues intrinsic to FL, such as transparency and privacy preservation. This integration improves the model's interpretability by resolving issues with the opacity of various machine-learning techniques.

Training process: In the training process, local models, each specializing in different mental health tasks, are independently trained on different datasets. A federated learning approach facilitates aggregating knowledge from these localized models to create a unified global privacy-preserving model. NCMs enhance this process by appropriately capturing mental health relationships' inherent uncertainty and dynamic nature and providing a comprehensive and nuanced understanding. This algorithmic fusion creates a robust foundation for our research and offers innovative solutions to the complex problems of mental health data analysis.

3.2 Data Generation:

The dataset used in this study was generated to aid in capturing the presence of indeterminate relationships that affect the various aspects of mental health. A dataset was curated using existing literature and basic datasets available. It is designed to gather comprehensive information on mental health, it included more diversity to enhance the generalizability of research findings to broader contexts.

The following attributes were considered *feeling_nervous, panic, breathing_rapidly, sweating, trouble_in_concentration, having_trouble_in_sleeping, having_trouble_with_work, hopelessness, anger, over_react, change_in_eating, suicidal_thought, feeling_tired, close_friend, social_media_addiction, weight_gain, introvert, popping_up_stressful_memory, having_nightmares, avoids_people_or_activities, feeling_negative, trouble_in_attention, blaming_yourself, hallucinations, repetitive_behaviour,* and *increased_energy.*

The data was labelled into *Attention-Deficit/Hyperactivity Disorder (ADHD), anxiety, Autism Spectrum Disorder (ASD), bipolar, eating disorder, loneliness, Major Depressive Disorder (MDD), Obsessive-Compulsive Disorder (OCD), Pervasive Developmental Disorders (PDD), psychotic depression, Post-Traumatic Stress Disorder (PTSD)* and *sleeping disorder.*

Over 600 records were generated based on the available regular mental health dataset, with indeterminacy introduced into the records to enable the creation of NCMs.

3.3 Data Preprocessing:

The collected data underwent a preprocessing phase to enhance its quality and reliability. Data cleaning procedures involved identifying and addressing inconsistencies, outliers, and inaccuracies in the dataset. Through careful validation and verification processes, erroneous entries were rectified or removed, ensuring a robust foundation for subsequent analyses. Normalization techniques were applied to ensure uniformity in the scale of numerical attributes. This step facilitates fair comparisons between different features, preventing any particular attribute from dominating the analysis due to its scale. Standardization ensured that all numerical features contributed equally to the modelling process, preventing bias in subsequent machine-learning algorithms. Efficient strategies were employed to handle missing values in the dataset. Missing data points were identified, and appropriate imputation methods were applied based on the nature of the missing information. This meticulous handling of missing values contributes to the completeness and reliability of the dataset used in the research.

3.4 Integration of Components

The seamless integration of these elements ensures a cohesive and collaborative system. The progression from data collection through preprocessing, collaborative training, iterative refinement, and evaluation establishes a robust foundation for predicting mental health conditions. The decentralized approach, facilitated by local models and a shared database, promotes adaptability and privacy in the learning process. This modular architecture is meticulously designed to tackle the multifaceted challenges in mental health prediction, providing a systematic and organized approach to enhance decision support through the fusion of federated learning and NCMs.

Figure 1 demonstrates a decentralized, federated learning approach for the collaborative development of NCMs while preserving data privacy. Independent participants encode customized NCMs on their local confidential data to model domain-specific concepts and interrelationships. Without sharing raw data, participants broadcast derivative model updates containing only parameters and weights to an aggregation server. Using multi-party computation protocols focused on the representational inclusivity of contributors, the server consolidates the collective model updates into an integrated consensus NCM. This federated NCM further undergoes auditing on various criteria to generate feedback for participants to enhance their localized models. Through iterative coordinated cycles of private simulation, anonymous aggregated orchestration and guided refinement, participants can strategically evolve personalized NCMs trained on their data while aligning with learnings from the collective federation.

4. Results and discussions

The data was separated into training and testing datasets and distributed across four local databases. Since there are over 600 records, 400 records were used for training the NCMs, one hundred at each local database. The remaining 200 records were used for testing, 50 each in the local database, to check if the updating of the local and global NCMs is happening.

Since 26 symptoms and 12 diseases are under consideration, visualization of the complete NCM might not be feasible. Simple NCMs are created at each local database level. If a symptom occurs in most cases of a particular disease, it is mapped to 1; otherwise, if it is indeterminate or has an uncertain effect on the disease, it is mapped to *I* in the local NCM.

Creation of global model: Edge weights in the global NCM are created based on the number of records considered for egde weight creation at the local NCM. The NCMs from the local database are aggregated to create the global NCM according to the weightage (number of cases considered) for each disease to update its NCM; once the NCMs are created, they can be updated. Whenever a local update occurs, it aggregates the updates, and the edge weights are altered accordingly, triggering a global model update.

The global model consists of aggregated values across the map to create a complete system with a mapping of all the symptoms and diseases. Whenever local updates occur, the local model updates are aggregated and used to update the global model; an expert for quality assesses them before the global model is updated.

Since the visualization is too massive to show, samples of the complete graphs are shown in Figures 2 and 3. These samples are obtained from the local database's NCM model, which was created using a part of the sample data. These figures pertain to the training data and are not universal in nature. For example, if anyone has attention span troubles, it does not imply concentration troubles or psychotic depression. They pertain to the representation of the dataset. This model shows that the relationship between sweating and psychotic depression is indeterminate; likewise, the relationship between stressful memory recall and anxiety is indeterminate.

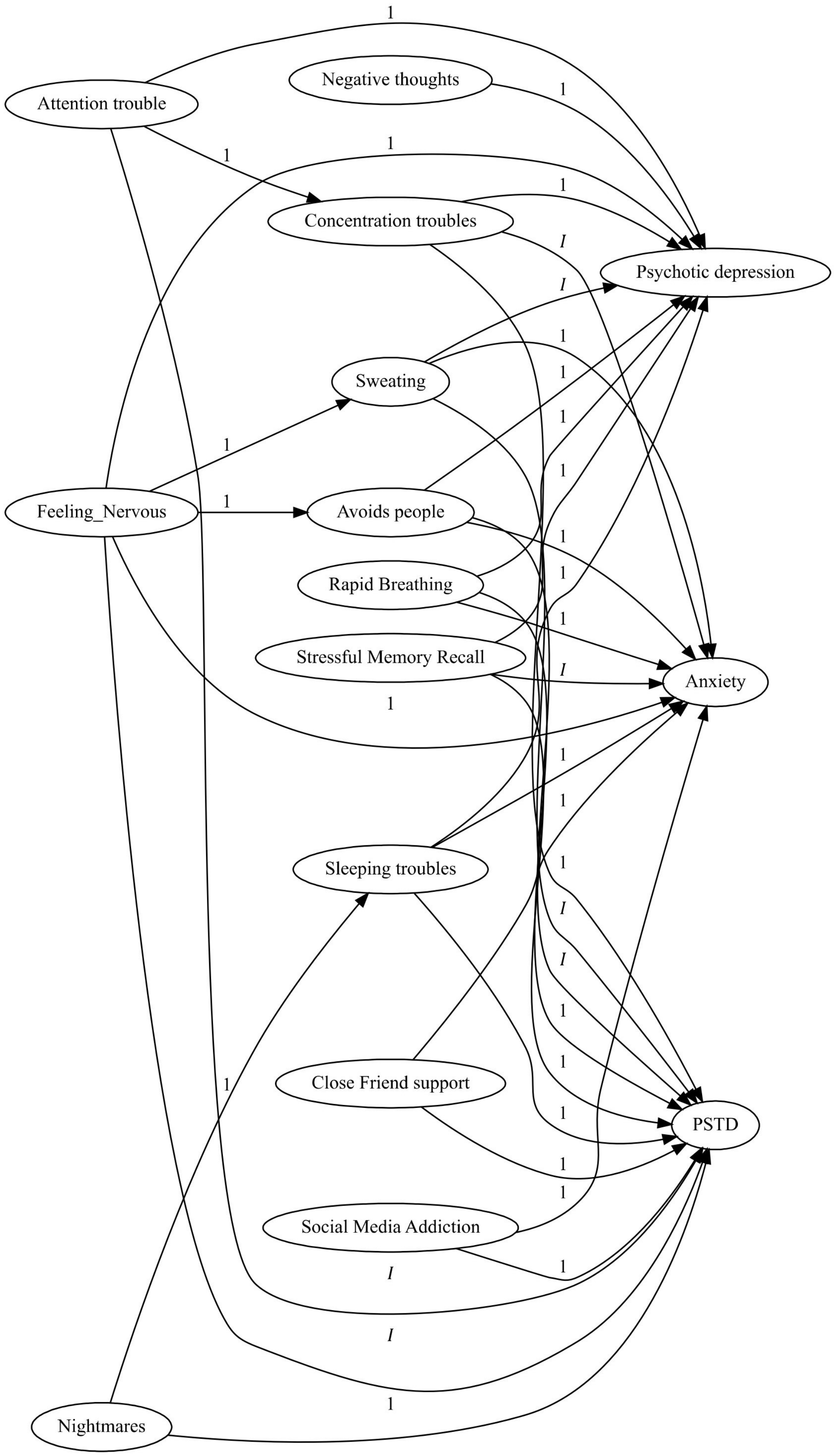

Figure 2: Part of the sample NCMs from the local database related to Anxiety, PSTD and psychotic depression.

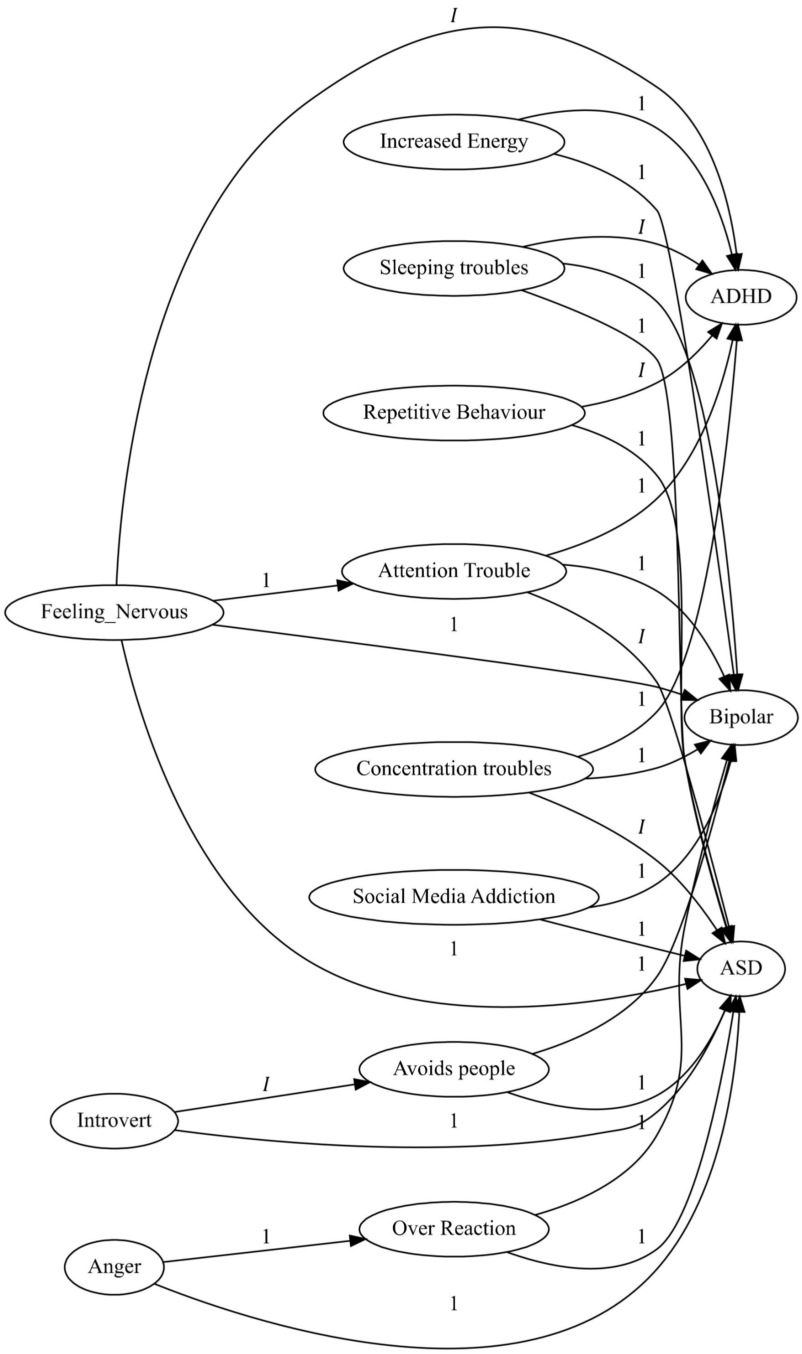

Figure 3 Part of the sample NCMs from the local database related to ADHD, ASD and Bipolar.

While considering symptoms and disease as given in Figure 3, it is seen that feeling nervous has an indeterminate effect on ADHD; similarly, being introverted has an indeterminate effect on avoiding people. Anger in general or for a general person anger can lead to overreaction, but anger → overreaction → ASD is not true, without the other symptoms. The presence of a combination of symptoms only results in a particular disease. The capturing of indeterminate relationships has made the data more sensitive in representation.

5. Conclusion and Future Enhancement

Complex uncertainties and interdependencies in clinical contexts related to mental health are difficult to fully capture. Hence, the training and testing are done on synthetic diagnosis outcome data. Since this data is limited, this model has validity concerns. In essence, federated modelling aligns NCM development with ethical imperatives around decentralization, privacy, security, and accessibility. It propagates collective knowledge from multifaceted domains in an inclusive ecosystem with sound data governance.

The resulting models can map multidimensional interactions underlying psychiatric conditions to inform personalized interventions. However, extensive testing is imperative to validate the effectiveness of noisy real-world applications. While the approach could transform crowdsourced insights for complex healthcare challenges, numerous extensions around security, ethics and engineering robustness are critical - including support for secure computations, blockchain-powered trust mechanisms, enhanced explainability and bias mitigation techniques.

This work presents a novel decentralized architecture that preserves data privacy while enabling safe and reliable mental health forecasts by integrating federated learning with NCM. This method allows for cooperative NCM training on private patient data dispersed among various sites without transferring data. NCMs offer interpretable insights and efficiently model correlations between symptoms and mental health states. This research fosters collaboration and trustworthy AI that respects privacy demands, making substantial progress towards developing ethical and practical AI solutions for mental health treatment. To facilitate data-driven decision-making, interpretable NCM models additionally allow a nuanced investigation of the links between various psychological concepts.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Data Availability: The authors can be contacted to obtain the data used.

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Received: Jan 2, 2024. Accepted: Mar 27, 2024