Federated Convolutional Neural Networks for Predictive Analysis of Traumatic Brain Injury: Advancements in Decentralized Health Monitoring

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***Abstract*—Traumatic Brain Injury (TBI) is a significant global health concern, often leading to long-term disabilities and cognitive impairments. Accurate and timely diagnosis of TBI is crucial for effective treatment and management. In this paper, we propose a novel federated convolutional neural network (FedCNN) framework for predictive analysis of TBI in decentralized health monitoring. The framework is implemented in Python, leveraging three diverse datasets: CQ500, RSNA, and CENTER-TBI, each containing annotated brain CT images associated with TBI. The methodology encompasses data preprocessing, feature extraction using gray level co-occurrence matrix (GLCM), feature selection employing the Grasshopper Optimization Algorithm (GOA), and classification using FedCNN. Our approach achieves superior performance compared to existing methods such as DANN, RF and DT, and LSTM, with an accuracy of 99.2%, surpassing other approaches by 1.6%. The FedCNN framework offers decentralized privacy-preserving training across individual networks while sharing model parameters with a central server, ensuring data privacy and decentralization in health monitoring. Evaluation metrics including accuracy, precision, recall, and F1-score demonstrate the effectiveness of our approach in accurately classifying normal and abnormal brain CT images associated with TBI. The ROC analysis further validates the discriminative ability of the FedCNN framework, highlighting its potential as an advanced tool for TBI diagnosis. Our study contributes to the field of decentralized health monitoring by providing a reliable and efficient approach for TBI management, offering significant advancements in patient care and healthcare management. Future research could explore extending the FedCNN framework to incorporate additional modalities and datasets, as well as integrating advanced deep learning architectures and optimization algorithms to further improve performance and scalability in healthcare applications.**

Keywords*—Traumatic brain injury; federated learning; convolutional neural network; grasshopper optimization algorithm; health monitoring

I. Introduction

Traumatic brain injury (TBI) occurs when the brain becomes dysfunctional and neuropath logically damaged due to abrupt and either immediate or secondary external pressures, such as a bump, blow to the head, or another type of injury [1]. Traumatic brain injury can cause a major disturbance in the brain's regular operating, which may outcome in either short-term or long-term neurological impairments. Each year, millions of individuals worldwide are impacted by this invisible spreading, which has significant rates of illness as well as death [2]. According to estimates, there are 1.7 million traumatic brain injuries in the US each year, and lifetime hospital expenses associated with TBI are predicted to reach over $76.5 billion dollars. India has the largest prevalence of brain damage worldwide, in accordance with the Indian Head damage Foundation; most occurrences of mortality occur within a two-hour period of the accident, and one in seven TBI patients pass immediately [3].

Traumatic brain injury causes a diverse range of impairments that can alter regular brain activity and lead to behavioural, physical, mental, and cognitive impairments. Initial and additional damages are the most common categories for injuries that accompany traumatic brain injury since the consequences usually arise either immediately or indirectly following the event [4]. Basic accidents, including diffused axonal damage and intracranial, subdural, and extradural hemorrhage, are the immediate outcome of trauma. Abrupt exterior mechanical pressures have the potential for bursting blood vessels, causing blood to collect in the brain's cranial partitions and produce hemorrhage [5]. Depending on where in the brain material the hematoma occurs, it can be classified as an extra-axial or intra-axial hematoma. Subdural hemorrhaging, subarachnoid hemorrhage, intraventricular hemorrhage, and intracerebral hemorrhage are examples of intra-axial hemorrhages while epidural hemorrhage is an example of an extra-axial hemorrhage. In the initial year, approximately fifty percent of ICH patients die. The original damage can manifest in as little as one hundred milliseconds, and in the initial hours following its commencement, the patient's condition begins to deteriorate [6].

The development of additional complications, which include a range of molecules, chemical-based, inflamed, and changes in metabolism, can occur minutes to days following the main brain damage. The adult skull is a rigid container filled with blood, brain, and the cerebrospinal fluid that has an uninterrupted capacity [7]. According to the Monro–Kellie philosophy, the total of these three significant elements' volumes never changes. Consequently, the amount of a minimum one of the two elements should be decreased in conjunction with any rise in intracranial contents. Moreover, raised ICP levels will result from this possible volume rise. Because of the hematoma's enlargement within the stiff skull, blood and CSF will gradually move into the cerebral region [8]. Because of good treatment in accordance with the Monro-Kellie philosophy, the ICP values stay low throughout the early stages of hemorrhage development. Elevated intracranial pressure has been shown to have greater consequences, including midline displacement, brain hernia, and eventually death, by damaging different brain regions [9].

A medical disorder known as midline shifting can result from the uncontrolled ICP levels caused by the mass impact of hemorrhage which may relocate the centre of structures toward the sides of the brain. The midline, which is linear in typical, healthy individuals, may be thought of as an imagined middle line because of the uniformity of the brain's organization [10]. The amount of MLS is calculated by taking into account the movement of any one of each of the three brain midline frameworks: the pineal glands, third ventricular, or septum pellucidum from the optimum midline. The enlargement of brain structures is caused by the massive impact caused by hematoma, which raises the pressure inside the head and moves the brain out of its normal position. Death may result from this in the end. MLS is thus regarded as an effective indicator of the most adverse patient experiences following a traumatic brain injury and a substantial determinant of ICP [11].

Since non-contrast CT scanning is quick, accessible, and provides a clear distinction between brains and blood connective tissue, it is the technique favoured for the identification and treatment of traumatic brain injury in the acute situation. Finding a hemorrhage in the CT images and evaluating its three main components—location, volume, and size—are essential for making choices about the outcome [12]. The utilization of an exterior ventricle loss, an intrusive operation that is very prone to diseases and consequences, is the most appropriate option for monitoring ICP. Moreover, CT scans are required in order to identify elevated ICP because different healthcare environments lacking competent neurosurgeons and intrusive ICP surveillance [13]. Numerous studies demonstrate that accurate visual examination and manual calculation of TBI outcomes according to CT are labour-intensive, prone to mistake and misinterpretation due to inter- and intra-observer variability and require a lot of time [14]. The level of accuracy of measurement is crucial for making decisions and additional diagnosis, since the degree of movement is essential in determining the degree of brain injury [15].

By recognizing the characteristics that doctors often employ to diagnose abnormalities, an average CAD system aims to reduce false negative rates. The CAD systems can now execute a variety of image analysis techniques thanks to the always expanding research projects. To enhance the quality of the paper, incorporating cross-validation or external validation techniques would be beneficial. Specifically, employing k-fold cross-validation could help assess the robustness and generalizability of the proposed FedCNN framework across different subsets of the dataset. Additionally, external validation involving independent datasets from other sources or institutions could further validate the effectiveness of the framework in diverse real-world settings, providing more comprehensive evidence of its performance and applicability. Integrating such validation methods would strengthen the credibility and reliability of the study's findings, enhancing its overall quality and impact in the field of decentralized ent. These approaches help physicians identify health monitoring for Traumatic Brain Injury (TBI) managemy diseases, plan treatments, estimate risks, and evaluate prognoses. A number of CAD-based methods are suggested to identify abnormalities in the brain that are reflected in images utilizing various methods. These controlled or uncontrolled partially automated or completely autonomous techniques use machine learning or deep learning methods to improve precision and effectiveness, and they may be used to identify a single brain disorder or a combination of disorders.

The Key contributions of the paper is given as follows:

- The paper leverages three distinct datasets, namely the CQ500 dataset, the RSNA dataset, and the CENTER-TBI study dataset, each offering comprehensive collections of brain CT images annotated for various intracranial abnormalities associated with traumatic brain injury. This multi-centric and heterogeneous dataset approach enhances the robustness and generalizability of the proposed predictive analysis model.
- The adoption of gray level co-occurrence matrix for feature extraction enables the capture of statistical texture features essential for accurately classifying normal and abnormal brain CT images. This sophisticated feature extraction method contributes to the discrimination of subtle patterns and textures indicative of traumatic brain injury, thereby enhancing the model's predictive capabilities.
- The implementation of the Grasshopper Optimization Algorithm for feature selection addresses the curse of dimensionality and optimizes classification performance by identifying an optimal subset of features from the larger feature space. This novel

feature selection strategy ensures the selection of the most relevant and discriminative features, thereby improving the efficiency and accuracy of the predictive analysis model.

- The adoption of federated convolutional neural networks for classification facilitates decentralized privacy-preserving training, enabling individual networks to independently train their local CNN models on their respective datasets while sharing model parameters with a central server in iterative communication rounds. This decentralized health monitoring approach ensures data privacy and security while enabling collaborative learning and model improvement across diverse healthcare environments.
- The culmination of these contributions results in an accurate predictive analysis model capable of distinguishing normal and abnormal brain CT images associated with traumatic brain injury. By integrating innovative techniques for data preprocessing, feature extraction, feature selection, and classification within a decentralized health monitoring framework, the paper advances the state-of-the-art in predictive analysis of traumatic brain injury, offering significant benefits for patient care and treatment optimization.

The following portions of the chapter are organized as follows. Section II includes an overview of the literature on predictive analysis of traumatic brain injury. The problem statement for the study is presented in Section III. Section IV covers the recommended approach for predictive analysis of traumatic brain injury. Section V compares the method's efficacy to previous techniques, and the performance measures are displayed, along with an explanation of the results. Section VI describes the conclusion.

II. Related Works

Prior studies in the field of intracranial hemorrhage and traumatic brain injury diagnosis have mostly depended on CT scanning for quick recognition and identification of hemorrhagic areas but require skilled interpretation to identify ICH subtypes. Nevertheless, specific quantitative information such as the thickness and amount of bleeding that is required for predictive making decisions in critical care settings is frequently absent from CT scans. Recent research has suggested deep learning methods for quantitative evaluation and subtype identification in ICH in order to overcome these shortcomings. In order to discover subtype differences and outline ICH zones, these frameworks usually entail preprocessing processes such as transforming DICOM to NIfTI layout, then performing multi-class segmentation based on semantics and optimized classification neural networks. These approaches have demonstrated potential, but they are not beyond drawbacks. Among the difficulties include the restricted applicability to other datasets, the possibility of overfitting as a result of fine-tuning on a smaller scale information, and the reliance on well datasets with annotations for training, which can occasionally not be easily accessible. Furthermore, flexibility in responding to different clinical scenarios and imaging techniques may be limited by the dependence on models that have been trained. Furthermore, to ensure durability and therapeutic significance, extensive validation on bigger and more varied groups is required, even with high accuracy achieved. Furthermore, there is still room for improvement and investigation in the actual use as well as incorporation of these deep learning technologies into clinical processes, taking into account aspects like immediate processing and usability by medical practitioners without extensive training. Therefore, while these advancements offer promise in enhancing ICH diagnosis and treatment decision-making, continued research efforts are essential to address these limitations and realize the full potential of deep learning in this critical medical domain [16].

In the domain of mild traumatic brain injury, recent efforts have aimed to enhance patient management through the development of decision rules and predictive models. While traditional statistical techniques have been utilized to identify low-risk patients for discharge from the emergency department, machine learning approaches have been explored to potentially improve predictive accuracy. However, findings from a retrospective cohort study utilizing gradient boosted decision trees on CT-identified TBI patients failed to demonstrate clear advantages over traditional methods. Despite achieving respectable predictive values, the machine learning models exhibited similar specificity to traditional approaches and were developed on a smaller dataset due to the necessity of partitioning for training, calibration, and validation. Key predictors of deterioration remained consistent across methods, including Glasgow Coma Scale, injury severity, and the number of brain injuries. Limitations include the challenge of data partitioning and the absence of substantial improvements over established techniques, highlighting the need for future research to focus on developing models that offer discernible advantages in outcome prediction for this patient population. Additionally, the modest improvement in predictive performance may not justify the added complexity and resource requirements associated with machine learning methods, underscoring the importance of considering practical implementation and clinical utility in advancing predictive models for TBI management [17].

Although they are not very specific, clinical guidelines have been developed in an attempt to reduce the misuse of CT scans in cases of mild traumatic brain injury. While duplicating these criteria using machine learning models has showed promise, attaining balanced specificity and sensitivity is still a problem. A deep artificial neural network model and an instance hardness cutoff technique were used in a study aimed at pediatric populations to replicate the Pediatric Urgent Services Clinical Research Networks clinical criteria for CT scan requirement. There are still restrictions in place despite encouraging outcomes with significant specificity and sensitivity. The study's use of historical information from the PECARN research that took place between 2004 and 2006 raises the possibility of biases or mistakes, which might have an impact on the model's applicability to current patient populations or therapeutic settings. Additionally, even though the DANN model outperformed the PECARN clinical guidelines in terms of sensitivity and specificity, practical issues like model understanding and convenience of incorporation into workflows for clinical practice are still unsolved. Furthermore, the study's emphasis on juvenile groups could restrict the findings' relevance to adult populations, calling for additional investigation to confirm the model's effectiveness across a range of patient demographics. Consequently, even though the DANN model appears to have potential for increasing the use of CT scans in paediatric TBI patients, further research should focus on resolving these issues and guaranteeing the model's reliability and applicability in clinical settings [18].

Machine learning algorithms have become more and more important in the endeavour to forecast the results of treatment for individuals with traumatic brain injury. These algorithms make use of a variety of data sources, such as imaging indexes laboratory information, clinical parameters, and demographic factors. But even with these advances, there are still restrictions. In order to identify important determinants of in-hospital mortality and long-term survival, a study carried out in a tertiary trauma centre in Iran sought to construct reliable prediction models utilizing machine learning techniques. While some variables were found to be significant, there are some limitations to the findings, such as the possibility of biases from retrospective data collection and the exclusion of insufficient information, which may compromise the generalizability of the model. Furthermore, the study's dependence on an Iranian single-centre dataset would restrict the findings' generalizability to other patient groups or healthcare environments. In addition, even though machine learning algorithms demonstrated potential in forecasting both short- and long-term mortality, issues like interpretability of models and adaptability in clinical settings still need to be addressed. Therefore, even though machine learning has the potential to predict the outcomes of traumatic brain injury patients, these limitations must be addressed through bigger and more diversified datasets, prospective research, and improved model interpretability in order to assure reliable and clinically useful predictions for TBI therapy [19].

Investment in models that use machine learning has increased as a result of the need to precisely predict results for patients with severe brain injuries. The goal of such models is to enhance treatment regimens and perhaps provide significant economic advantages. Using admission information from 2,381 patients with severe traumatic brain injury as training data, researchers at Rajaee Hospital in Shiraz, Iran. Restrictions still exist despite the good performance with high levels of specificity, sensitivity, and precision. Particularly, using retrospective information collected from a single location may restrict generalizability to wider populations or healthcare environments and induce biases. Furthermore, the focus of the study on predicting positive or negative outcomes six months after the event may have obscured subtle differences in patient paths and long-term forecasts. Additionally, even though machine learning approaches have great potential, there are still issues with model comprehension, scaling, and the requirement for big and varied datasets [20].

Recent research in the domain of traumatic brain injury diagnosis and outcome prediction has witnessed significant advancements, particularly through the application of machine learning techniques. Studies have focused on enhancing the accuracy of intracranial hemorrhage detection and subtype classification using deep learning frameworks, although challenges such as dataset generalization and practical implementation remain. Additionally, efforts have been made to improve the prediction of treatment outcomes in TBI patients through ML algorithms, yet limitations persist in terms of model interpretability and generalizability across diverse patient populations. The sections that have been made available emphasise how crucial it is to use machine learning especially deep learning to solve practical difficulties with TBI diagnosis and treatment. The theoretical framework may be enhanced by integrating the knowledge from the literature review, with a focus on developing models that have higher specificity, sensitivity, and usability in order to further TBI research and improve patient outcomes. Furthermore, the development of clinical rules and predictive models for mild TBI has shown promise, but achieving balanced sensitivity and specificity remains a challenge. While machine learning approaches offer potential in optimizing treatment procedures and predicting clinical outcomes, addressing limitations such as biases from retrospective data collection, model interpretability, and scalability in clinical practice are crucial for realizing their full potential in TBI management.

III. Problem Statement

The limitations observed in previous research efforts regarding predictive analysis of traumatic brain injury prompt the necessity for innovative approaches. Existing studies have primarily focused on machine learning techniques, such as deep learning frameworks, for TBI diagnosis and outcome prediction. However, challenges persist in terms of dataset generalization, model interpretability, and scalability in clinical practice. Additionally, while efforts have been made to develop clinical rules and predictive models, achieving balanced sensitivity and specificity remains elusive [21]. Moreover, the reliance on retrospective data from single centers may introduce biases and limit the applicability of findings to broader patient populations or healthcare settings. In light of these challenges, our proposed paper aims to address these limitations by introducing a novel approach utilizing federated convolutional neural networks for predictive analysis of TBI. By leveraging federated learning techniques, we aim to overcome issues related to data privacy and centralization, enabling decentralized health monitoring while maintaining patient confidentiality. Through our proposed federated CNNs, we seek to enhance predictive accuracy and enable real-time monitoring of TBI patients across diverse healthcare environments, ultimately contributing to improved patient outcomes and healthcare delivery in the field of traumatic brain injury management.

IV. Methodology

Three major components make up the methodology presented in this paper: gathering data, preprocessing with median filtering, feature extraction with grey level co-occurrence matrix, feature selection with Grasshopper Optimization Algorithm, and classification with federated convolutional neural networks. For training and assessment, three different datasets are used: the CQ500 dataset, the

RSNA dataset, and the CENTER-TBI research dataset. All three provide extensive and varied sets of brain CT images labelled for different intracranial abnormalities related to traumatic brain injury. In preprocessing, noise is removed from CT images by median filtering, and then statistical texture characteristics necessary for differentiating between normal and pathological pictures are extracted using GLCM. The Grasshopper Optimization Algorithm is utilized for feature selection to overcome the dimensionality problem and enhance classification performance. This algorithm makes it easier to identify the best subset of features from the broader feature space. Lastly, federated CNNs are used for classification. These are decentralized, privacy-preserving training mechanisms that allow separate networks (A, B, and C) to train their local CNN models independently on their own datasets and share parameter values with a central server through iterative communication rounds. By combining updated parameters from local models, the global CNN model continuously improves through this federated learning setup. This leads to an understanding of features that differentiate between normal and abnormal images across all networks, enabling accurate predictive analysis of traumatic brain injury while maintaining data privacy and decentralization in health monitoring. Fig. 1 shows the overview of the proposed architecture.

A. Data Collections

1) Dataset for Network A: Most of the research that have been done so far have employed smaller datasets that were gathered from individual institutions in an effort to establish computer-aided diagnosis systems that can identify various disorders connected to traumatic brain injury. A publicly accessible brain CT dataset called CQ500 can help with the creation of machine learning algorithms that classify and recognize different types of abnormalities in the brain [22]. The creation of general, computerized CAD systems to evaluate the many anomalies connected to traumatic brain injury is made easier by these multicentre and heterogeneity datasets. 491 brain CT images from various radiology units have been collected batch-wise and combined into the varied CQ500 dataset by the Centre for Advanced Research in Images, Neurosciences and Genomics, located in New Delhi, India. Three separate radiologists interpreted each CT image to determine whether or whether each had (i) ICH and its five forms, (ii) midline shift, (iii) calvarias fractures, and (ICH age and afflicted brain hemisphere. An example of the dataset's normal and aberrant images is displayed in Fig. 2.

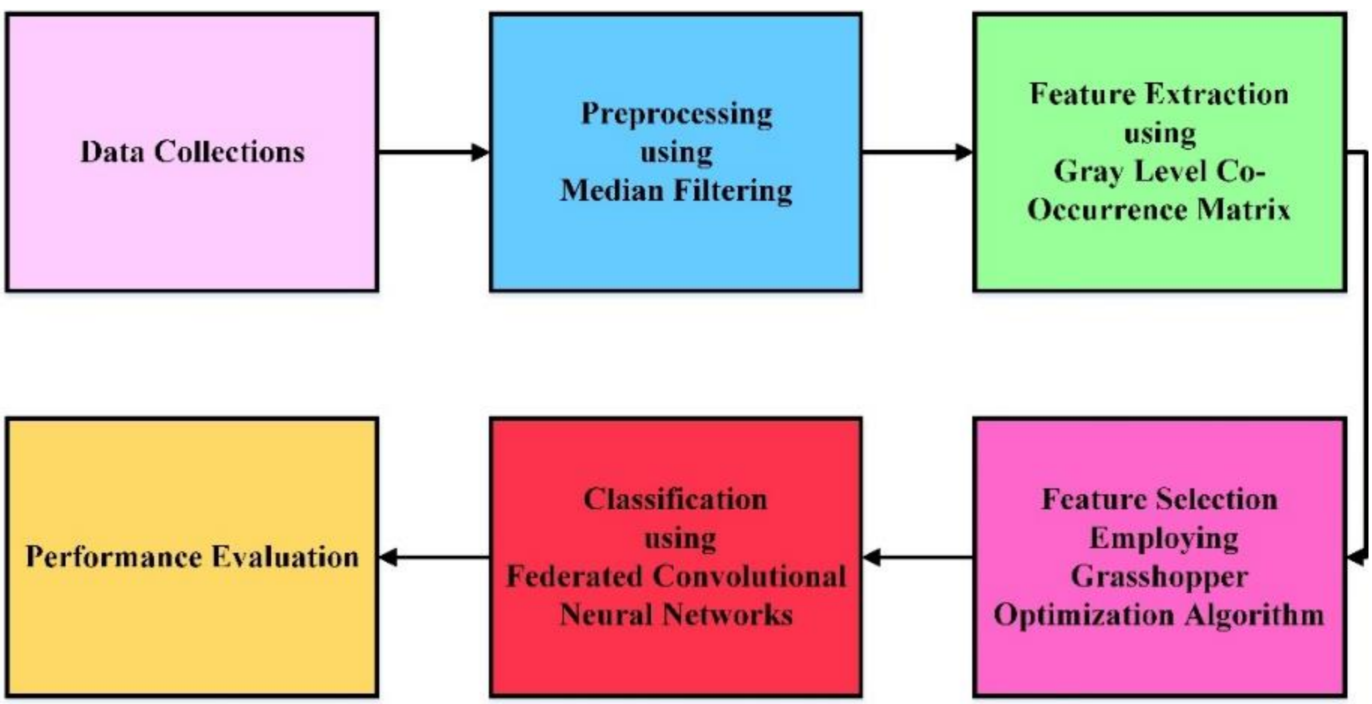


Fig. 1. Overview of the proposed architecture.

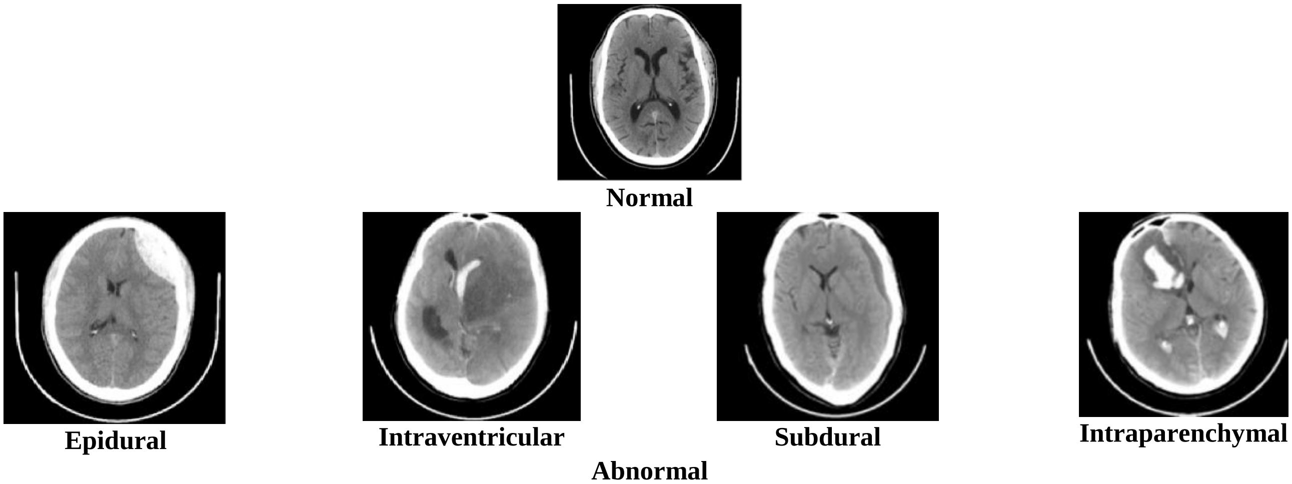


Fig. 2. Sample CT images from CQ500 dataset.

2) Dataset for network B: The RSNA dataset, which includes 865,032 labeled brain CT images for hemorrhage identification and categorization, is the biggest publicly accessible dataset. Experienced radiologists have analyzed each CT scan in this multinational and multi-institutional dataset for the existence or lack of each of the five forms of ICH. 652,403 and 123,133 CT images, accordingly, constitute the training and test information. There is a group imbalance among the hemorrhage subgroups [23].

3) Dataset for network C: The study utilized information from the CENTER-TBI, which enrolled more than 5000 individuals from a variety of facilities, including community hospitals, trauma groups, and university medical centers. Three layers of information are gathered, each distinguished by a particular care path: The following three patient groups are classified as follows: 1) individuals seen in the emergency department and released; 2) patients transferred to the medical facility but not to an intensive care unit and 3) patients transferred to the ICU. A CT scan was conducted in accordance with standard clinical practice on a clinical scanner with a wide range of imaging variables. For the purpose of assessing the segmentation of immediate intracranial lesions, three unique subcohorts of the CENTERTBI information set are taken into consideration: cistern identification and midline shift estimate. This guarantees that each data set provides a significant variety when it comes to of TBI severity and imaging parameters of interest [24].

B. Preprocessing using Median Filtering

Pre-processing is used to eliminate extraneous information from brain CT scans, which can create noise and negatively impact CAD system performance. The improved CT images in this investigation were obtained by using a median filter. The speckle noise in a CT picture is eliminated using the median filter. In digital image processing, noise is eliminated by using a median filter. This novel approach uses a median filter for filtering in order to identify traumatic brain damage. A neighbourhood region serves as the filtering window for the median filtering method, which modifies its size based on certain filtering process setup criteria. A useful technique that can separate out of varied isolates from acceptable picture alternatives like boundaries and characteristics to a certain degree is the median filter. In particular, the median filter substitutes the median for a pixel rather than the neighbourhood's average of all the pixels Ψ. As could possibly see in Eq. (1).

$$M[R(u)+S(u)] \neq M[R(u)]+M[S(u)] \quad (1)$$

A statistically based non-linear signal processing technique is the median filter. The noisy number will be replaced with the digital image's median value. The noisy value is replaced by the group median, which is saved after the mask's pixels are arranged according to the gray levels.

C. Feature Extraction using Gray Level Co-Occurrence Matrix

Characteristics are the bits of data that are important for representing important aspects of pictures and for solving certain applications. The selection of input characteristics greatly affects training set parameters and categorization accuracy. The technique of extracting an image's visual content in order to reduce the number of resources needed is known as feature extraction. Gray level co-occurrence matrix (GLCM) was developed in this study to extract statistical texture information. Texture characteristics are significant low-level characteristics that are utilized to measure an image's perceived texture and define its contents.

The widely used GLCM method uses statistical distributions of intensity value combinations at various locations in relation to one another in an image to determine second order statistical texture characteristics. There are three categories of statistics: first, second, and higher order, based on the quantity of intensity locations within the image. Although theoretically feasible, the computational cost prevents the implementation of higher levels statistics. Texture characteristics hold details about the surface's structural organization and how it interacts with its surroundings. Energy, correlation, entropy, homogeneity, sum variability, autocorrelation, contrary, maximal probability, dissimilarity, IDM normalized, and many more texture-based characteristics are acquired—a total of twenty-two are obtained. Some of them are expressed as follows:

1) Energy: Energy can also be defined as "angular second moment" or "uniformity." It provides the GLCM matrix's sum of square components. From homogeneous to non-homogeneous regions, it is done this way. When the frequency of repeated picture pixels is high, it is high. Eq. (2) displays the energy equation.

$$E = \sum_{u,v=0}^{m-1} (Q_x)^2 \quad (2)$$

2) Entropy: It determines the image's unpredictability. A uniform image will therefore provide a lower entropy rating. Eq. (3) displays the entropy equation.

$$ET = \sum_{u,v=0}^{m-1} -In(Q_x)\, Q_x \quad (3)$$

3) Contrast: It determines the strength of the contrasts that connects a pixel to its neighbour throughout the whole image. Eq. (4) displays the equation of contrast.

$$C = \sum_{u,v=0}^{m-1} Q_x (u-v)^2 \quad (4)$$

4) Correlation: It measures the linear gray tone dependency of a picture. It explains how a pixel and its neighbour are linked. The correlation equation is shown in Eq. (5).

$$Co = \sum_{u,v=0}^{m-1} Q_x \frac{(u-\mu*v-\mu)}{\sigma^2} \quad (5)$$

5) Homogeneity: It measures the degree of pixel resemblance. The homogenous image's GLCM matrix values out to 1. If the texture of the image just needs minor adjustments, it is very low. Eq. (6) displays the equation of homogeneity.

$$H = \sum_{u,v=0}^{m-1} \frac{Q_x}{1+(u-v)^2} \quad (6)$$

D. Feature Selection Employing Grasshopper Optimization Algorithm

While characteristics are necessary to achieve high accuracy, an abundance of characteristics can lead to a "dimensionality curse" whereby an excessive number of characteristics wastes a significant amount of storage capacity, increases calculation time, and complicates categorization. Adding more characteristics also increased the risk of "overfitting," which reduces the system's generalizability and reduces accuracy. Therefore, it is necessary to create feature selection strategies, which choose the "optimal subset of features" from a wider set. The Grasshopper Optimization Algorithm is used in this work to choose characteristics.

In 2016, the GOA algorithms was introduced. This method emulates the natural swarming behaviour of grasshoppers. Three factors influence a grasshopper's position in a swarm's flight path: wind advection (B_u), gravity (H_u), and social interaction (R_u). Eq. (7) defines the social interaction as the primary search mechanism in the GOA algorithm.

$$R_u = \sum_{v=1,v\neq u}^{M} r(c_{uv})\widehat{c_{uv}} \quad (7)$$

In this case, r denotes a function that defines the degree of societal pressures, $c_{uv} = |y_v - y_u|$ is the distance that exists between the u-th and v-th grasshoppers, and $\widehat{c_{uv}} = \frac{y_v = y_u}{c_{uv}}$ is the vector of units from the u-th grasshopper to the v-th grasshopper. The above equation shows that the function of r is the primary element of the relationship between people. Eq. (8) specifies the value of this function, which determines a grasshopper's orientation of travel within the swarm.

$$r(s) = fe^{\frac{-s}{l}} - e^{-s} \quad (8)$$

where, l is the attracting distance scales and f is the attraction's strength. The grasshoppers are driven by this function to repel one another as well as to be attracted to one another. In order to prevent colliding, two grasshoppers will repel one another when their distances are within the range of [0, 2.079]. To keep the swarm cohesive, the attraction force grows while the distance is in [2.079, 4]. The zone of comfort is the region where there cannot be a pressure at precisely 2.079.

In the event when the distance between them equals 2.079, both attraction and repulsion vanish. From 2.079 units of distance until almost four the attraction intensity rises and then progressively falls. Substantial differences in the values of the variables in the equation used for the value of s (l and f) result in altered swarming behaviour. To demonstrate how grasshoppers communicate with regard to their comfort zones. When it comes to modelling grasshopper interactions, the swarm approach performs well. But in order to create an optimization algorithm, it has to be modified. The subsequent mathematical representation of the search during grasshopper interactions was suggested by the study. Eq. (9) serves as a representation of the computational framework.

$$Y_u^c = b\left(\sum_{v=1,v\neq u}^{M} b\frac{ia_c - la_c}{r} r(|y_v^c - y_u^c|)\frac{y_v - y_u}{c_{uv}}\right) + \widehat{T}_c \quad (9)$$

where, ($\widehat{T}_c$) is the average value of the c-th dimensions in the objective (best solution discovered so far), c is a diminishing parameter to shorten the comfort region, repelling region, and attractiveness region, and ia_c is the maximum value in the c-th dimensions and la_c is the lowest limit in the c−th dimensions. The following equation illustrates how the swarm modifies the location around an objective $\widehat{T}_c$. The swarm is brought closer to the target by the parameter c. The goal in the GOA algorithms is thought to be the most effective approach found thus far. When an improved technique is found, the best approach becomes revised while the grasshoppers communicate and pursue the objective.

Eq. (10) is utilized to modify variable c, which is the primary governing variable in the GOA algorithm.

$$d = d_{max} - l\frac{d_{max} - d_{min}}{L} \quad (10)$$

where, d_{max} = 1, and d_{min}= 0.00001, L is the greatest number of iterations, and l is the present repetition.

E. Classification using Federated Convolutional Neural Networks

With federated learning, client edges could discover a common global model without sending their confidential local information to a central server. Federated learning is a developing distributed privacy-protection learning method. Every training cycle, the local machine receives a model that everyone uses from the cloud-based global servers, training it using each user's personal information, and then updates the weights or gradients by sending a request back to the servers. The client-uploaded models are combined on the server to create an additional global design. The following distinguishing characteristics of federated learning set it apart from conventional centralized learning:

1) The global server clouds cannot access the training data since they are dispersed on local edges. All clients and the serves share the same learning model, nevertheless.

2) Rather than on the server, model training takes place on each local device. In order to create a shared global model, the server compiles the local models that the clients contribute, sends the completed model returned to the clients.

3) Compared to typical centralized learning, federated learning requires a lot more local computing power and capabilities.

The process of federated learning is described, in which every client trains its unique local algorithm utilizing its own information after receiving the parameters of the larger framework from the central server. Following local training, every local device transmits its learned local variables to the server, where they are combined to create a revised global model that will be utilized for training in the subsequent iteration of training. In federated learning, the time patterns, or so-called communication phases, are indicated by the subscript *t*.

Convolutional neural networks have demonstrated consistently higher effectiveness for image categorization and are appropriate to handle very high dimensional inputs. CNN topological architectures are comparable. Three different types of layers are often found in a CNN: convolutional, pooling, and fully linked layers. Many kernel filters, which can be identified as an array of square block neurons, make up the convolutional layer. The preceding layer's kernel filters, which may be thought of as training weights, are subjected to "convolution" processes by the convolutional layer. The CNN may be explained mathematically in the following way in Eq. (11).

$$x_{uv}^{l} = \sigma\left(\sum_{g=0}^{m-1} \sum_{h=0}^{m-1} f_{gh} y_{(u+g)(v+h)}^{i-1}\right) \tag{11}$$

Here, y^{l-1} is the convolutional layer's input, x_{uv}^{l} is its output, l is the layer number, f_{gh} is a n × n kernel filter, and σ is the activation constant. The study specifically uses the corrected linear unit (relu) as the function that activates of the hidden neuron to mitigate the effects of softmax function and gradient vanishing in nodes that produce data for multi-class categorization problems. Below are the Eq. (12) and (13) for the softmax and relu functions.

$$\sigma_{relu}(k) = \max(0, k) \tag{12}$$

$$\sigma_{softmax}(k_u) = \frac{exp(k_u)}{\sum_{u=1}^{D} exp(k_u)} \tag{13}$$

where, C is the overall amount of label categories that require to be classified and k is the result of the preceding layer. The amount of label categories that require classification. After many convolutional layers of the CNN, a pooling layer can be implemented to extract certain features from hidden representation. In order to improve the representation characteristics of filtered pictures from the preceding convolutional layer, a measurement of m × m Max pooling windows is often built for obtaining the maximum brightness value of pixels inside the associated Max pooling windows region. A typical alternative to the Max pooling procedure is the Average pooling approach, which involves average value distribution of features throughout the window region. The flattening image pixels from the result of the layer before it provides the input for the fully linked layer, which is applied at the rear of the CNN. This layer's primary function is to categorize the characteristics that were retrieved from the CNN's earlier layers into different groups. Fig. 3 illustrates how federated CNN operates.

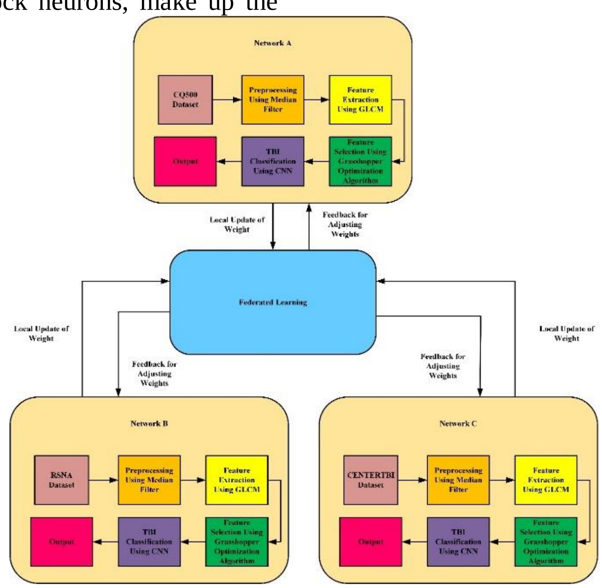


Fig. 3. Working of federated CNN.

In the federated CNN mechanism for classifying images as normal or abnormal, each network (A, B, and C) possesses its own dataset containing a mix of normal and abnormal images. In the federated learning setup, during each communication round, the central server sends the parameters of the global CNN model to each network. Subsequently, each network independently trains its local CNN model using its respective dataset, leveraging the local computational resources and privacy-preserving nature of federated learning. The CNN model consists of convolutional layers, pooling layers, and fully connected layers for extracting and classifying features from the images. After local training, the updated parameters of the local CNN models are sent back to the central server, where they are aggregated to form an updated global CNN model. This global model represents a collective understanding of the features distinguishing normal and abnormal images across all networks. The process iterates over multiple communication rounds, with the global model continuously improving its ability to classify images accurately while respecting data privacy constraints inherent in federated learning.

V. Results and Discussion

In this section, the study presents the results and discussion of the proposed paper. The methodology encompasses data collection from three diverse datasets: the CQ500 dataset, the RSNA dataset, and the CENTER-TBI study dataset, each containing annotated brain CT images associated with traumatic brain injury. Preprocessing involves median filtering for noise removal, followed by feature extraction using gray level co-occurrence matrix to capture statistical texture features. Feature selection is conducted employing the Grasshopper Optimization Algorithm to optimize classification performance by identifying an optimal subset of features. Classification is performed using federated CNNs, enabling decentralized privacy-preserving training across individual networks (A, B, and C) while sharing model parameters with a central server. Through federated learning, the global CNN model evolves iteratively, aggregating updated parameters from local models to achieve a collective understanding of features distinguishing normal and abnormal images, thus enabling accurate predictive analysis of traumatic brain injury while ensuring data privacy and decentralization in health monitoring.

A. Performance Evaluation

Assessment measures are required to evaluate the predictive accuracy. The most common approach for accomplishing this is to determine accuracy. The percentage of datasets detected correctly by a classifier indicates its accuracy for a specific testing dataset. Because employing basically the accuracy metric cannot be used for optimal decision-making. The recommended technique's performance was evaluated utilizing precision, recall, accuracy, and F1-score measurements. The following describes the definitions of each measure:

- The term T_{pos} (True Positive) describes the total amount of accurately found data.
- The term $Fpos$ (False Positive) refers to the proportion of accurate data that was mistakenly detected.
- False negatives (F_{neg}) occur when erroneous data is mistakenly recognized as legitimate.
- Identification of erroneous information values is known as T_{neg} (True Negative).
- T_{neg} (True Negative) is used to identify inaccurate data entries.

1) Accuracy: The classifier's accuracy indicates the extent to which it generates the correct prediction. Accuracy is measured by the ratio of reliable projections compared to all alternative reasonable projections. It is demonstrated by Eq. (14).

$$Accuracy = \frac{T_{pos}+T_{neg}}{T_{pos}+T_{neg}+F_{pos}+F_{neg}} \tag{14}$$

2) Precision: The number of properly detected results is calculated by determining a classifier's precision, or its degree of accuracy. Accuracy improvement results in reduced false positives, but lower precision causes numerous additional errors. Precision is defined as the percentage of examples that correlate appropriately to all incidences. It is defined by Eq. (15).

$$P = \frac{Tpos}{Tpos+Fpos} \tag{15}$$

3) Recall: The degree of sensitivity of a recognition, or the amount of relevant information produced, is determined by recall. Enhanced recall decreases the total quantity ofF_{neg}. Recall is the proportion of properly classified instances to all projected events. This is demonstrable by Eq. (16).

$$R = \frac{Tpos}{Tpos+Fneg} \tag{16}$$

4) F1-Score: The F1-Score, which represents the weighted average of recall and accuracy, is calculated by summing both recall and precision. It is characterized by Eq. (17).

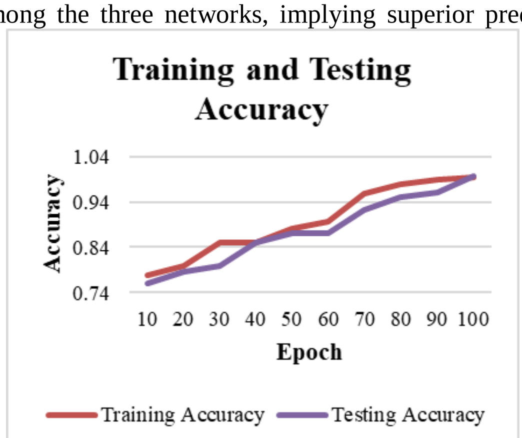
$$F1 - Score = \frac{2\times precision \times recall}{precision\times recall} \tag{17}$$

5) ROC Curve: In deep learning and machine learning, the area under the ROC curve, or AUC, is a well-known statistic for binary classification problems. The binary recognition algorithm's efficacy is measured by the area under the curve, which is visually depicted by the Receiver Operating Characteristic curve. The classifier in a binary classified problem looks for information that indicates whether a division is positive or negative.

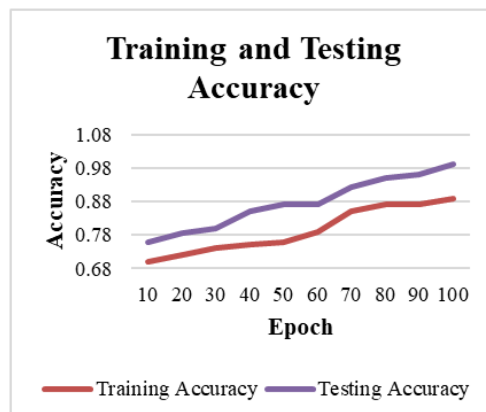
Fig. 4 depicts the training and testing accuracy for Network A, Network B, Network C, and the Centralized Server in the proposed federated CNN framework for predictive analysis of traumatic brain injury. In (a), (b), and (c), the training accuracy gradually increases with each communication round, indicating that the local CNN models for each network (A, B, and C) improve over successive iterations. Similarly, the testing accuracy follows an upward trend, signifying enhanced classification performance on unseen data as the federated learning process advances. Notably, Network B demonstrates the highest testing accuracy among the three networks, suggesting superior predictive capability in identifying normal and abnormal brain CT images associated with traumatic brain injury. In contrast, (d) illustrates the training and testing accuracy of the Centralized Server, showcasing a comparable performance to the federated networks, albeit with a single global model trained on aggregated data. Overall, it highlights the effectiveness of federated CNNs in achieving accurate predictive analysis of traumatic brain injury while preserving data privacy and decentralization across multiple networks.

Fig. 5 illustrates the training and testing loss for Network A, Network B, Network C, and the Centralized Server within the federated CNN framework for predictive analysis of traumatic brain injury. In (a), (b), and (c), the training loss gradually decreases over successive communication rounds, indicating improved convergence of the local CNN models for each network (A, B, and C). Similarly, the testing loss exhibits a downward trend, suggesting enhanced generalization performance on unseen data as the federated learning process advances. Notably, Network B demonstrates the lowest testing loss among the three networks, implying superior predictive capability in differentiating between normal and abnormal brain CT images associated with traumatic brain injury. In contrast, (d) presents the training and testing loss of the Centralized Server, showcasing comparable performance to the federated networks, albeit with a single global model trained on aggregated data. Overall, Fig. 5 highlights the efficacy of federated CNNs in achieving accurate predictive analysis of traumatic brain injury while ensuring data privacy and decentralization across multiple networks.

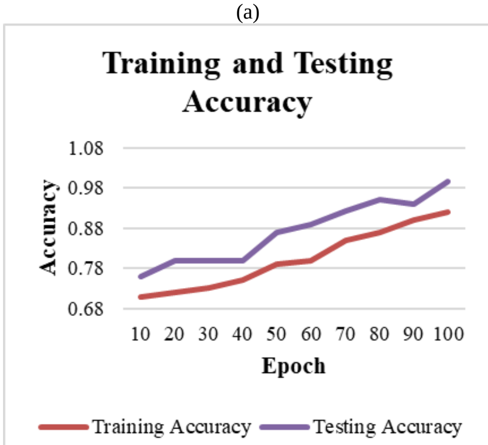
Fig. 6 depicts the fitness of the Grasshopper Optimization Algorithm utilized for feature selection in the proposed federated convolutional neural network framework for traumatic brain injury predictive analysis. The plot illustrates the convergence of the GOA algorithm over successive iterations, with the fitness value gradually improving towards optimization. As the number of iterations increases, the fitness value decreases, indicating the algorithm's effectiveness in identifying an optimal subset of features from the larger feature space. The diminishing fitness curve reflects the algorithm's ability to iteratively refine feature selection, ultimately enhancing the classification performance of the CNN models. This visualization underscores the utility of the GOA in mitigating the curse of dimensionality and optimizing feature representation for accurate TBI predictive analysis within the federated learning paradigm.



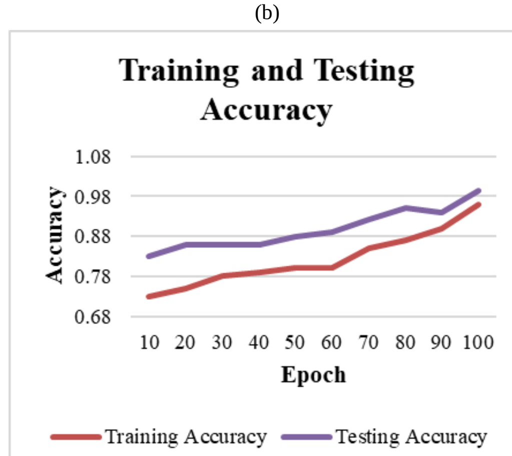
(a)



(b)

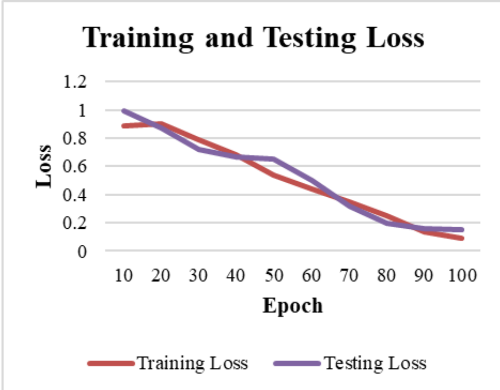


(c)

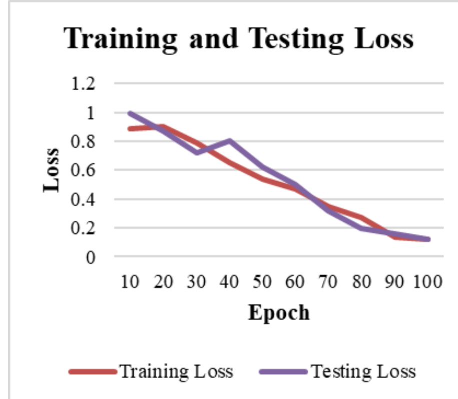


(d)

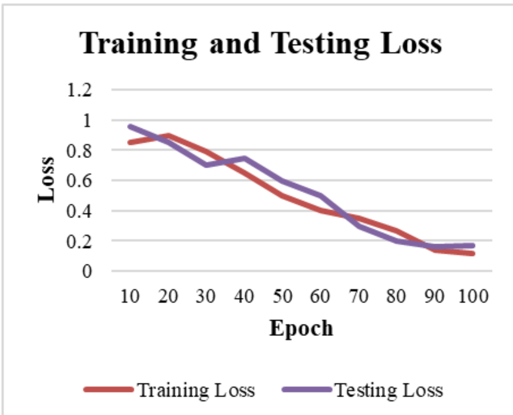
Fig. 4. Training and testing accuracy (a) Network A (b) Network B (c) Network C and (d) Centralized server.



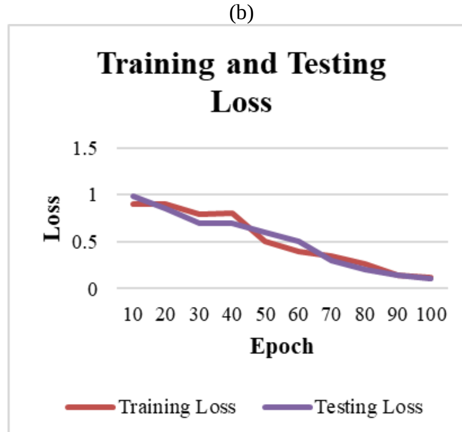
(a)



(b)



(c)



(d)

Fig. 5. Training and testing loss (a) Network A (b) Network B (c) Network C and (d) Centralized server.

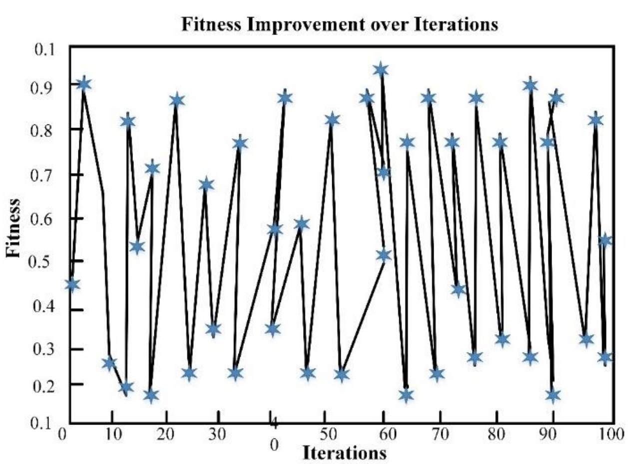


Fig. 6. Fitness of the grasshopper optimization algorithm.

Fig. 7 presents the Receiver Operating Characteristic graphs for each network (A, B, and C) and the centralized server in the proposed federated convolutional neural network framework for predictive analysis of traumatic brain injury. The ROC curves plot the true positive rate against the false positive rate for varying classification thresholds, providing a comprehensive assessment of model performance across different operating points. Each curve represents the trade-off between sensitivity and specificity, with a higher area under the curve indicative of better discriminative ability. The curves illustrate the CNN models' capacity to distinguish between normal and abnormal brain CT images, with steeper slopes and greater AUC values reflecting superior predictive accuracy. By comparing the ROC curves of individual networks with the centralized server, the graph evaluates the efficacy of federated learning in achieving comparable performance to centralized approaches while preserving data privacy and decentralization. The ROC analysis offers insights into the CNN models' classification performance and underscores the framework's utility in facilitating accurate TBI predictive analysis in decentralized health monitoring settings.

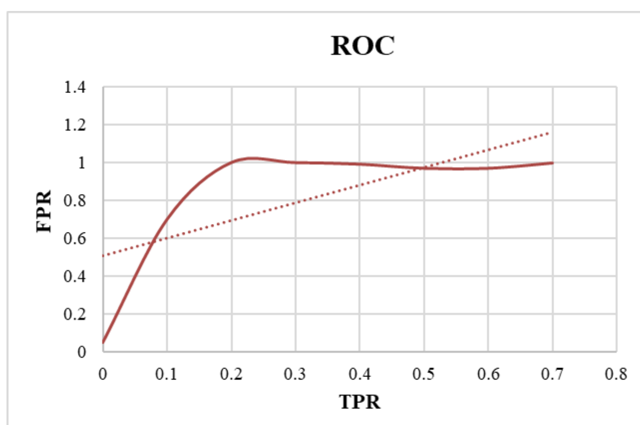


Fig. 7. ROC graph.

TABLE I. COMPARISON OF THE DATASETS IN THE PROPOSED SYSTEM

Datasets	Accuracy (%)
CQ500	98.7
RSNA	99.5
CENTER-TBI	97.6

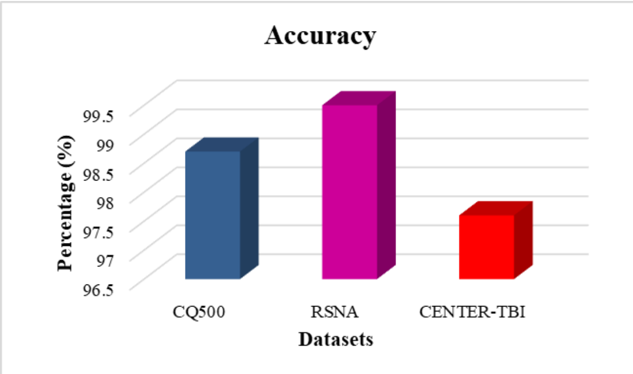


Fig. 8. Comparison of the datasets in the proposed system.

Table I and Fig. 8 provides a comparative overview of the datasets utilized in the proposed federated convolutional neural network system for predictive analysis of traumatic brain injury. The table lists three datasets: CQ500, RSNA, and CENTER-TBI, along with their corresponding accuracy percentages. The CQ500 dataset achieves an accuracy of 98.7%, followed by RSNA with 99.5%, and CENTER-TBI with 97.6%. These accuracy scores reflect the performance of the CNN models trained on each dataset in accurately classifying brain CT images as normal or abnormal, thereby demonstrating the efficacy of the proposed system across diverse datasets with varying characteristics. The table underscores the robustness and generalizability of the federated CNN framework in achieving high predictive accuracy for TBI diagnosis while leveraging heterogeneous data sources, thus facilitating reliable decentralized health monitoring for TBI management.

Table II and Fig. 9 presents a comprehensive comparison of performance metrics between the proposed federated convolutional neural network (FedCNN) method and other existing approaches for predictive analysis of traumatic brain injury. The table includes four methods: DANN, RF and DT, LSTM, and the proposed FedCNN, with corresponding metrics of accuracy, precision, recall, and F1-score expressed in percentage values. Among the compared methods, the proposed FedCNN demonstrates superior performance across all metrics, achieving an accuracy of 99.2%, precision of 99.1%, recall of 99.1%, and F1-score of 99.1%. This indicates the efficacy of the FedCNN approach in accurately classifying brain CT images as normal or abnormal, surpassing the performance of alternative methods such as DANN, RF and DT, and LSTM. The higher performance metrics of the proposed FedCNN underscore its potential as an advanced and reliable tool for TBI diagnosis and predictive analysis, thus offering significant advancements in decentralized health monitoring and clinical decision-making in TBI management.

TABLE II. EVALUATION OF THE PROPOSED METHOD'S PERFORMANCE METRICS IN COMPARISON WITH OTHER CURRENT STRATEGIES

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DANN [18]	97.2	97.4	97.4	97.4
RF and DT [19]	95.6	96.2	95.3	95.5
LSTM [25]	98.7	98.5	98.7	98.3
Proposed FedCNN	99.2	99.1	99.1	99.1

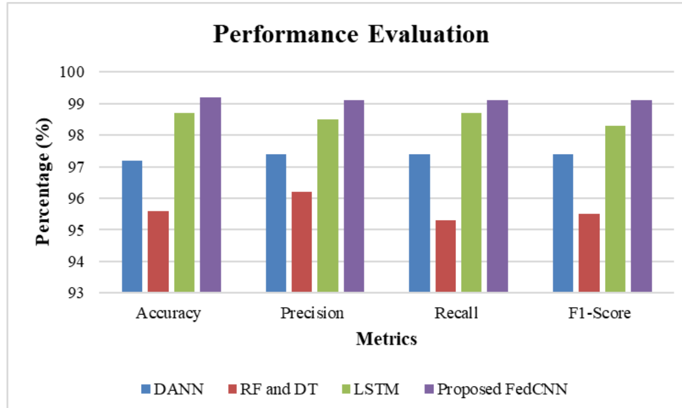


Fig. 9. Comparison of the performance metrics of the proposed method with other existing approaches.

B. Discussion

The results presented in this study showcase the effectiveness of the proposed federated convolutional neural network framework for predictive analysis of traumatic brain injury in decentralized health monitoring. Leveraging three diverse datasets, namely CQ500, RSNA, and CENTER-TBI, the FedCNN framework demonstrates robust performance in accurately classifying brain CT images as normal or abnormal across multiple networks (A, B, and C) while ensuring data privacy and decentralization. The evaluation metrics including accuracy, precision, recall, and F1-score indicate superior performance of the FedCNN approach compared to existing methods such as DANN [18], RF and DT [19], and LSTM [25]. The FedCNN achieves remarkable accuracy scores, with Network B exhibiting the highest testing accuracy among the three networks. Additionally, the Grasshopper Optimization Algorithm effectively optimizes feature selection, mitigating the curse of dimensionality and enhancing classification performance. ROC analysis further confirms the FedCNN's discriminative ability, with steeper slopes and higher AUC values reflecting superior predictive accuracy. These findings underscore the FedCNN's potential as an advanced tool for TBI diagnosis, offering significant advancements in decentralized health monitoring and clinical decision-making while preserving data privacy and decentralization. Overall, the results validate the efficacy and reliability of the proposed FedCNN framework in facilitating accurate TBI predictive analysis, thereby contributing to improved patient outcomes and healthcare management in TBI scenarios. Integrating more sophisticated deep learning architectures and optimization techniques could potentially further optimize the FedCNN framework's performance and scalability in broader healthcare applications while broadening its scope to include a wider range of modalities and datasets could greatly improve its adaptability in addressing various TBI scenarios. However, it is essential to acknowledge the limitations that are intrinsic to this research. The usefulness of the FedCNN may be limited by small and homogenous annotated datasets, requiring efforts to expand and diversify the data sources. Furthermore, overcoming the computational complexity of feature extraction and selection techniques is necessary to guarantee effective scalability, and managing legal and privacy issues in decentralized health monitoring systems is essential to encouraging the FedCNN approach's broad acceptance and application in actual healthcare settings.

VI. Conclusion and Future Scope

In conclusion, this study presents a novel federated convolutional neural network (FedCNN) framework for predictive analysis of traumatic brain injury in decentralized health monitoring. Leveraging three diverse datasets and employing preprocessing, feature extraction, feature selection, and classification techniques, the proposed FedCNN framework achieves remarkable accuracy in classifying brain CT images as normal or abnormal while ensuring data privacy and decentralization. The results demonstrate superior performance of the FedCNN approach compared to existing methods, indicating its potential as an advanced tool for TBI diagnosis and clinical decision-making. Moreover, the Grasshopper Optimization Algorithm effectively optimizes feature selection, enhancing classification performance and mitigating the curse of dimensionality. The ROC analysis confirms the FedCNN's discriminative ability, further validating its efficacy in TBI predictive analysis. The study contributes to the field of decentralized health monitoring by providing a reliable and efficient approach for TBI management, offering significant advancements in patient care and healthcare management. For future research, further exploration could focus on extending the FedCNN framework to incorporate additional modalities and datasets, such as MRI and EEG data, to enhance the accuracy and scope of TBI diagnosis. Additionally, investigating the integration of advanced deep learning architectures and optimization algorithms could further improve the FedCNN's performance and scalability. Moreover, exploring the application of federated learning techniques in other healthcare domains beyond TBI could broaden the impact of decentralized health monitoring, paving the way for more comprehensive and personalized healthcare solutions. Overall, the proposed FedCNN framework holds promise for revolutionizing TBI diagnosis and healthcare management, offering a scalable and privacy-preserving approach for decentralized health monitoring in diverse clinical settings.

References

[1] A. I. Maas et al., "Traumatic brain injury: progress and challenges in prevention, clinical care, and research," The Lancet Neurology, vol. 21, no. 11, pp. 1004–1060, 2022.

[2] J. Haarbauer-Krupa, M. J. Pugh, E. M. Prager, N. Harmon, J. Wolfe, and K. Yaffe, "Epidemiology of chronic effects of traumatic brain injury," Journal of neurotrauma, vol. 38, no. 23, pp. 3235–3247, 2021.

[3] A. K. Wagner et al., "Traumatic brain injury," in Braddom's Physical Medicine and Rehabilitation, Elsevier, 2021, pp. 916–953.

[4] B. L. Brett, R. C. Gardner, J. Godbout, K. Dams-O'Connor, and C. D. Keene, "Traumatic brain injury and risk of neurodegenerative disorder," Biological psychiatry, vol. 91, no. 5, pp. 498–507, 2022.

[5] J. R. Howlett, L. D. Nelson, and M. B. Stein, "Mental health consequences of traumatic brain injury," Biological psychiatry, vol. 91, no. 5, pp. 413–420, 2022.

[6] D. Khayatan et al., "Protective effects of curcumin against traumatic brain injury," Biomedicine & Pharmacotherapy, vol. 154, p. 113621, 2022.

[7] D. Y. Madhok et al., "Outcomes in patients with mild traumatic brain injury without acute intracranial traumatic injury," JAMA network open, vol. 5, no. 8, pp. e2223245–e2223245, 2022.

[8] I. Thomas et al., "Serum metabolome associated with severity of acute traumatic brain injury," Nature communications, vol. 13, no. 1, p. 2545, 2022.

[9] C. A. Åkerlund et al., "Clustering identifies endotypes of traumatic brain injury in an intensive care cohort: a CENTER-TBI study," Critical care, vol. 26, no. 1, p. 228, 2022.

[10] J. Tjerkaski et al., "Extended analysis of axonal injuries detected using magnetic resonance imaging in critically Ill traumatic brain injury patients," Journal of Neurotrauma, vol. 39, no. 1–2, pp. 58–66, 2022.

[11] A. Drieu et al., "Persistent neuroinflammation and behavioural deficits after single mild traumatic brain injury," Journal of Cerebral Blood Flow & Metabolism, vol. 42, no. 12, pp. 2216–2229, 2022.

[12] A. Z. Mohamed, P. J. Nestor, P. Cumming, F. A. Nasrallah, and A. D. N. Initiative, "Traumatic brain injury fast-forwards Alzheimer's pathology: evidence from amyloid positron emission tomorgraphy imaging," Journal of neurology, vol. 269, no. 2, pp. 873–884, 2022.

[13] L. Papa et al., "Evaluation of glial and neuronal blood biomarkers compared with clinical decision rules in assessing the need for computed tomography in patients with mild traumatic brain injury," JAMA Network Open, vol. 5, no. 3, pp. e221302–e221302, 2022.

[14] J. H. Park et al., "Glymphatic system evaluation using diffusion tensor imaging in patients with traumatic brain injury," Neuroradiology, vol. 65, no. 3, pp. 551–557, 2023.

[15] A. M. Janas et al., "Diffuse axonal injury grade on early MRI is associated with worse outcome in children with moderate-severe traumatic brain injury," Neurocritical care, vol. 36, no. 2, pp. 492–503, 2022.

[16] A. Phaphuangwittayakul, Y. Guo, F. Ying, A. Y. Dawod, S. Angkurawaranon, and C. Angkurawaranon, "An optimal deep learning framework for multi-type hemorrhagic lesions detection and quantification in head CT images for traumatic brain injury," Applied Intelligence, pp. 1–19, 2022.

[17] C. Marincowitz, L. Paton, F. Lecky, and P. Tiffin, "Predicting need for hospital admission in patients with traumatic brain injury or skull fractures identified on CT imaging: a machine learning approach," Emergency Medicine Journal, vol. 39, no. 5, pp. 394–401, 2022.

[18] H. Ellethy, S. S. Chandra, and F. A. Nasrallah, "Deep neural networks predict the need for CT in pediatric mild traumatic brain injury: A corroboration of the PECARN rule," Journal of the American College of Radiology, vol. 19, no. 6, pp. 769–778, 2022.

[19] H. Khalili et al., "Prognosis prediction in traumatic brain injury patients using machine learning algorithms," Scientific reports, vol. 13, no. 1, p. 960, 2023.

[20] M. Nourelahi, F. Dadboud, H. Khalili, A. Niakan, and H. Parsaei, "A machine learning model for predicting favorable outcome in severe traumatic brain injury patients after 6 months," Acute and critical care, vol. 37, no. 1, pp. 45–52, 2022.

[21] A. I. Maas et al., "Traumatic brain injury: progress and challenges in prevention, clinical care, and research," The Lancet Neurology, vol. 21, no. 11, pp. 1004–1060, 2022.

[22] S. Chilamkurthy et al., "Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study," The Lancet, vol. 392, no. 10162, pp. 2388–2396, 2018.

[23] A. E. Flanders et al., "Construction of a machine learning dataset through collaboration: the RSNA 2019 brain CT hemorrhage challenge," Radiology: Artificial Intelligence, vol. 2, no. 3, p. e190211, 2020.

[24] S. Jain et al., "Automatic quantification of computed tomography features in acute traumatic brain injury," Journal of neurotrauma, vol. 36, no. 11, pp. 1794–1803, 2019.

[25] C. Q. Lai, H. Ibrahim, A. I. A. Hamid, and J. M. Abdullah, "LSTM network as a screening tool to detect moderate traumatic brain injury from resting-state electroencephalogram," Expert Systems with Applications, vol. 198, p. 116761, 2022.