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Optimized Federated Learning Algorithm for Breast Cancer Detection Using the Marine Predators Algorithm

Journal of Electrical Systems

Abstract: - Breast cancer stands as the leading cause of cancer-related fatalities among women worldwide, necessitating effective detection methods. However, the current landscape of breast cancer detection poses several challenges, including high costs, complexity, and suboptimal accuracy rates. In response, this paper presents a pioneering approach to breast cancer detection leveraging federated learning, a paradigm that allows model training across distributed data sources without centralized data sharing. Central to this novel detection model is the integration of a Convolutional Neural Network (CNN) architecture and a meta-heuristic optimization algorithm known as the marine predator's algorithm (MPA). CNNs have emerged as powerful tools for biomedical image analysis, enabling automatic feature extraction crucial for detecting abnormalities in medical images. However, optimizing CNNs for detection tasks requires meticulous tuning of hyperparameters across different layers, a process impractical to perform manually due to its complexity and time-intensive nature. To address this challenge, the paper proposes the utilization of the MPA as an optimization algorithm within the federated learning framework. The MPA, inspired by the foraging behaviour of marine predators, enhances the exploration-exploitation trade-off to prevent the model from getting stuck in local optima during training. By incorporating the MPA into the CNN architecture, the proposed model achieves remarkable testing accuracy, surpassing the performance of traditional DCNN models. During testing, the proposed model attained an impressive accuracy rate of 98.32%, showcasing its superior performance compared to the DCNN model, which achieved a 95.95% accuracy. Moreover, the proposed approach outperforms existing algorithms, achieving an accuracy rate of 98%. These results underscore the effectiveness of the federated learning-based approach in enhancing breast cancer detection accuracy. the proposed breast cancer detection model represents a significant advancement in the field, offering a highly accurate and efficient solution to overcome the challenges associated with traditional detection methods. By leveraging federated learning and innovative optimization techniques, this model holds promise for improving early detection rates, ultimately contributing to better patient outcomes in the fight against breast cancer.

Keywords: Breast Cancer, Federated Learning, CNN, DCNN, Random-forest, Deep Learning

I. INTRODUCTION

Breast cancer, a prevalent malignancy in women, stands as the second most common cause of female mortality. The global incidence of breast cancer continues to rise, with an increasing number of reported cases annually. Unlike many other malignancies, it disproportionately affects women. Untimely detection of this disease poses a significant risk of fatality [1]. Timely identification significantly enhances the prospects of successful treatment and survival. However, the diagnosis process is time-consuming and often involves subjective evaluations by pathologists. The integration of Computer-Aided diagnosis (CAD) systems holds promise for improving diagnostic accuracy. Breast cancer is categorized into benign (non-hazardous) and malignant (threatening) types. Early detection and distinguishing between malignant and benign lesions play a pivotal role in determining breast cancer prognosis [2]. Globally, breast cancer impacts approximately a million women each year, representing over 25% of all female cancer cases. Automatic breast cancer detection in its early stages presents several challenges, including the varied features of images and the differing sizes of cells. Processing these features and effectively mapping them poses a bottleneck issue for deep learning algorithms [3,4,5]. The presence of multiple feature variants can exacerbate training errors, particularly within fully connected layers. To address this, optimization processes are employed to control the rate of error maximization. These optimization techniques often utilize algorithms such as gradient descent and swarm intelligence-based approaches like particle swarm optimization. By implementing optimization algorithms, training errors can be minimized, thereby enhancing detection ratios. Despite improvements in the training process, several challenges persist, prompting authors to propose enhanced models of convolutional neural

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networks (CNNs)[6,6,7,8]. Surveys suggest that the Deep Convolutional Neural Network (DCNN) is the most prominent algorithm for breast cancer detection. DCNN represents an improved version of the traditional CNN algorithm. Additionally, alternative learning approaches, such as ensemble methods and transfer learning, have significantly contributed to the early-stage detection of breast cancer. These approaches leverage the collective intelligence of multiple models or pre-trained networks to enhance detection accuracy and robustness. recently, research efforts have primarily concentrated on advancing algorithms rather than enhancing datasets. Prior observations have indicated that achieving or nearing 100% accuracy in training sets is feasible through continuous training with datasets like CBIS-DDSM [10-15]. The current deep convolutional networks demonstrate sufficient efficacy for classifying CBIS-DDSM datasets. However, it's crucial to recognize that histopathological data presents a more intricate and varied landscape compared to controlled experimental settings. This complexity underscores the necessity for broader and more diverse datasets to enhance the generalizability and robustness of practical application models. Yet, obtaining such extensive and varied medical data, especially breast histopathological images, is constrained by privacy regulations that prohibit collection and exchange outside hospital settings. Adequate high-quality data is indispensable for effectively training machine learning models. Unfortunately, medical datasets often grapple with issues like uneven distribution and insufficient data due to the challenges of collection. Consequently, the conflict between safeguarding privacy and fulfilling the demands for comprehensive data fusion poses a significant impediment to the advancement of intelligent healthcare systems. In addressing this confusion, a method that focuses on amalgamating knowledge derived from data rather than amalgamating the data itself, known as federated learning, emerges as a fitting approach for the evolution of intelligent medical diagnostic systems [20-24]. To tackle the challenge of feature optimization and training errors in deep learning algorithms, a novel approach has been proposed. This approach combines feature optimization using the marine predator's algorithm and integrates it with the federated learning approach of transfer learning. Federated learning employs a distributed learning algorithm, leveraging distributed systems to enhance the detection ratio of breast cancer. The key contributions of this algorithm can be summarized as follows:

1. This paper proposes a early stage breast cancer detection.
2. The proposed algorithm based on federated learning and marine predators' algorithm; algorithm reduces training errors of model.
3. The proposed algorithm compares existing algorithm of breast cancer such as random forest, DCNN, hybrid and CNN.
4. Merine predator's algorithm optimized hyper-parameters of FL algorithm.

the remainder of this paper is structured as follows: Sect. II presents some related work. Section III explains proposed methodology. Section IV presents the experimental analysis Section V introduces details of result analysis. Finally, Sect. VI concludes this paper and presents future directions.

II. RELATED WORK

Breast cancer detection has garnered significant attention, given its status as one of the leading causes of death among women. Efforts in medical imaging systems aim to enhance the automatic diagnosis of breast cancer in its early stages. Various authors have recently put forth deep learning and advanced learning methodologies to address this challenge. This section provides a concise overview of the latest algorithmic contributions in this field. [1] aims to create high-quality images for spotting cancerous areas in pictures. The major goal of enhancement is to create high-quality images for spotting cancerous areas in pictures. Compare the results to the filters currently in use. In the end, the suggested technique outperforms existing algorithms with an accuracy of 98%. in [2] explores numerous deep learning models and the procedures for using them to identify cancer. We conducted a rigorous analysis and summary of recent advancements in deep learning algorithms for cancer diagnosis to identify significant obstacles in their application for precise early cancer detection. In [3], a retrained CNN model named ResNet50 was utilised in the proposed strategy. The proposed strategy utilizes a retrained CNN model named ResNet50 residual network. Combining the IMPA algorithm with this model creates the IMPA-ResNet50 architecture. [4] employee deep learning techniques, data accessibility, and various breast cancer screening procedures such as mammography, thermography, ultrasound, and magnetic resonance imaging. We provide an overview of deep learning techniques, data accessibility, and several breast cancer screening procedures like mammography, thermography, ultrasound, and magnetic resonance imaging. In [5], the mammography method makes use of early breast cancer detection. Researchers gathered the images from various established mammogram datasets. Performance data show that the predicted system performs better than the most advanced methods. In [6], the authors employed the CNN model, and CNN's effectiveness ultimately resulted in a 97.65% accurate diagnosis of benign and malignant tissues. The suggested strategy greatly increased the speed, accuracy, and precision of the categorization. In [7], the application is set up in accordance with the "breast cancer" specific form of cancer. The report highlights six widely used image-based deep learning models, such as fully convolutional networks, deep belief networks, and convolutional neural networks. In [8], the authors focus on how radiologists can recommend further examinations of abnormal mammograms and develop the most effective treatment plans. Based on the experimental results, radiologists can prescribe more examinations of abnormal mammograms and provide the best possible treatment plan. The proposed hybrid AI model has the potential to considerably distinguish between benign and malignant breast tissues. [9] believes that the evaluation performance of the suggested framework might be encouraging, with 98.50% accuracy, 98.06% sensitivity, 98.99% specificity, and 98.98% precision. Such performance appears to benefit the development of a useful and trustworthy computer-aided diagnostic (CAD) framework for breast cancer categorization. In [10], strong augmentation-based SSL- techniques for mammography-screening breast cancer diagnosis They have created an algorithm to adapt recent strong augmentation-based SSL techniques for mammography-screening breast cancer diagnosis. SSL boosts a model's performance by instructing it to extract features from unlabeled samples. Researchers found specific alterations appropriate for the mammography images. [11] provides an overview of using DL with multiple-imaging modality radionics data. In particular, we work with medical pictures from positron emission tomography (PET), magnetic resonance imaging (MRI), digital breast tomography (DBT), mammography, ultrasonography (US), and histology to characterise breast cancer. in [12] With an emphasis on deep learning, this study will examine current computational and digital pathology techniques for the diagnosis of breast cancer. The paper begins by reviewing public databases pertaining to breast cancer diagnosis. The study also provides a summary of current deep learning techniques for diagnosing breast cancer. In [13], the model that utilised the same architecture for all three perspectives fared the best after two models with different architectures were built and tested. When the clinical data decision was added, its accuracy increased from 85.4% to 93.8%. In [14], extensive experimentation has validated the effectiveness of our suggested strategy. They used a dataset of 600 mammograms of female patients. The experiments evaluate the precision of our suggested strategy for detection and categorization. The model achieves 98.53% accuracy in detecting cancer, 95.6% in detecting benign conditions, and 95% in detecting normal patients. In [15], compared to other techniques that require sophisticated equipment, thermal imaging is a superior alternative that enables machines to provide clinics and hospitals with a simpler and more efficient approach. In [16], the suggested multitask segmentation strategy is compared to a fully convolutional neural network and the multitask U-net, and the F-scores get better by an average of 2,88% and 9,78%, respectively. In [17], a ViT-based ensemble backbone network is utilised for binary and multi-class diagnosis, resulting in a prediction improvement of 8.1% and 6.2%, respectively, showcasing the effectiveness of the suggested hybrid ETECADx. When the ViT-based ensemble backbone network is used by 8.1% and 6.2% for binary and multi-class diagnosis, respectively, the suggested hybrid ETECADx demonstrates further prediction improvement. For validation purposes, the suggested CAD system offers encouraging prediction accuracies of 97.16% for binary and 89.40% for multi-class, utilizing real breast pictures. in [18] The term „LR-PCA" refers to a brand-new hybrid processing method built on Logistic Regression (LR) and Principal Components Analysis (PCA). This type of procedure aids in the identification of important principle components (PCs) for further use in classification. In [19], the accuracy rates for this approach were 96.42% (Mini-MIAS), 95.49% (DDSM), and 96.92% (BCDR). For three publicly accessible datasets, the KM++CSO approach yielded 96.27% accuracy on overage. Additionally, the detection results included a Jaccard Index Score of 91.05%. In [20], examine different CNN models, such as ResNet-50, VGG-16, Alex Net, and Google Net, to detect malignancy in mammography scans. We'll also create a unique Xception model with 70% accuracy to diagnose breast cancer and compare it to the other models. [21] intends to compare ML and DL approaches for detecting and diagnosing breast cancer. The accuracy and F1-score of Random Forest (tuned) were 96.66% and 0.963, respectively, according to experimental data, outperforming all other models. In an effort to develop a reliable method for identifying and categorising breast cancer, this article examined 93 distinct references that have been discussed in the processing area in recent years. According to the findings of this study, the majority of today's effective methods emphasise the application of deep learning techniques. [23] suggests using Deep Belief Networks (DBN) in this study to diagnose breast cancer using ROI images. The accuracy, specificity, sensitivity, and precision performance rates of the suggested DBN model are 96.32%, 96.68%, 95.93%, and 96.40%, respectively. In [24], the Softmax layer in VGG makes the assumption that the training samples belong to exactly one class, which is untrue in practical applications like the diagnosis of medical images. To address this issue, researchers use SVM instead of VGG's softmax layer. Additionally, researchers use data augmentation to address the need for a large number of samples in DLA. In [26], a model named SSL-MMGCN, we assess

MMGCN's classification performance both separately and in combination with SSL-MG across several training environments. Compared to the multitask deep graph (GCN) approach, which had an AUC classification accuracy of 0.81, our results show that SSL-MNGCN and MMGCN are better at learning, with 0.97 and 0.98 AUC classification accuracy, respectively. In [27], we proposed a technique called DenTnet to categorise images of breast cancer histopathology in particular. We recommend using a technique called DenTnet to categorize images of breast cancer histopathology. DenTnet uses DenseNet as its foundational model to handle the problem of extracting features from the same distribution by applying the transfer learning principle.

III. PROPOSED METHODOLOGY

This section outlines the proposed methodology for breast cancer detection, which integrates a federated learning model with convolutional neural networks and the marine predators' algorithm. The marine predators' algorithm is utilized for hyper-parameter optimization and the optimization of feature maps within convolutional layers. In this methodology, the federated learning model aggregates local training data from breast cancer datasets and maps the feature data as benign or malignant. The algorithmic process is structured into three sections: Federated Learning Exploration: This section delves into the principles and implementation of federated learning, highlighting its role in aggregating and processing decentralized training data. Marine Predators Algorithm Exploration: Here, the marine predators' algorithm is examined in detail, focusing on its application in optimizing hyper-parameters and feature maps within convolutional layers. Proposed Algorithm Exploration: The final section synthesizes the federated learning model, convolutional neural networks, and the marine predators' algorithm, elucidating how they collectively contribute to the breast cancer detection process.

1st section

Federated Learning

Our study introduces a Federated Learning framework for breast cancer detection utilizing Convolutional Neural Networks (CNNs), with a specific focus on predicting breast cancer based on mammography datasets. The key innovation of our research lies in our emphasis on accurately processing data through transfer learning techniques. By leveraging robust data, we anticipate improved detection outcomes, leading to enhanced treatment rates for patients. We conducted evaluations with various models and identified the most suitable model for breast cancer detection based on the DDSM dataset. Federated learning, the cornerstone of our approach, operates as a decentralized machine learning paradigm. It facilitates model training across multiple devices or servers holding local data samples, without necessitating data exchange. This framework effectively distributes the learning process among edge devices, thereby safeguarding privacy and minimizing data movement requirements. The process of feature map training of DDMS cancer dataset present in figure(1)[31,33].

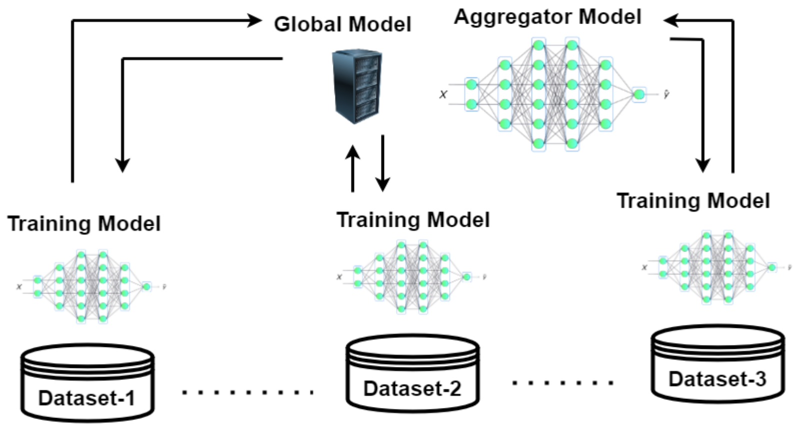

Figure 1 **model of federated learning approach in DDSM dataset**

2nd section

Marine Predators Algorithm

The inspiration for the Marine Predators Algorithm (MPA) stems from the natural foraging behavior observed in ocean predators and their interactions with prey. In this context, predators aim to optimize encounter rates to enhance their survival prospects in their natural environment. MPA employs two simple random walk methods, namely Levy flight and Brownian motion, to conduct searches. Levy flight, commonly utilized in meta-heuristic algorithms, is particularly effective in preventing solution stagnation by facilitating a constructive search in local areas. Additionally, Brownian motion serves as a well-established global search mechanism. The creators of MPA combined the search efficiency of Levy and Brownian motion to enhance the trade-off scale between exploration and exploitation. The process of function topology and objective space present in figure (2)[32].

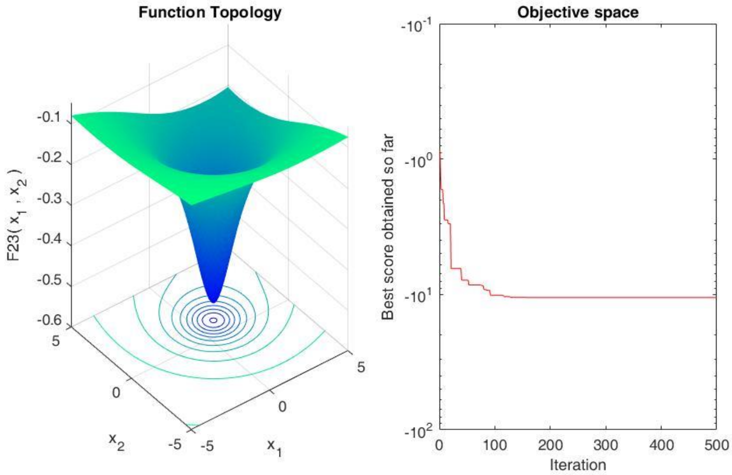

Figure 2 function topology and objective space of MPA

3rd section

Proposed Methodology

The proposed methodology revolves around a federated learning approach for training the DDSM dataset. In this design, local training models are integrated with convolutional neural networks (CNNs) and marine predators' algorithms (MPA). MPA serves as an optimizer for the CNN algorithms, enhancing the accuracy of processing while reducing training loss and improving prediction outcomes. The CNN networks employed in this methodology typically comprise three layers: convolutional layers, pooling layers, and fully connected layers. The convolutional layers extract features from the input data, the pooling layers, often utilizing max pooling, reduce the dimensionality of the feature map matrix derived from the DDSM dataset. This reduction in dimensionality helps streamline the computational process while retaining essential information for effective breast cancer detection. the combination of federated learning, CNNs, and MPA offers a robust framework for training on the DDSM dataset, enabling accurate prediction and efficient processing of breast cancer detection tasks. The processing of proposed algorithm present in figure(3).the processing of algorithm describes here.

Processing of algorithm for training of local dataset

Input: Local dataset Di = (Xi, ŷi), CNN, number of epochs, batch size

Output: Trained local model

procedure Local Model Training(Di, CNN, epochs, batch size

- Initialize local model: K
- for each epoch in 1 to epochs do
- Shuffle Di randomly
- for each batch in Di with batch size batch_size do
- Extract batch data: Xbatch, ŷbatch
- Compute predictions: ŷpred = Mi(Xbatch)
- Calculate loss: Lbatch = Loss(ŷbatch, ŷpred)
- Update model weights: i.update_weights(Lbatch)
- end for

- end for
- end procedure
- Return Trained local model Mi

Processing of training of global federated Model

Input: List of local datasets [D1, D2, ..., DN]

Input: Number of datasets N

Output: Global federated model Federated Model

- Initialize an empty list prediction
- for i from 1 to N do
- predictions ← Data_i_ predict(X)
- predictions.append(predictions_i)
- end for
- combined_predictions ← sum(predictions)
- final_predictions ← argmax(combined_predictions)
- Initialize the global federated model FederatedModel
- Return FederatedModel

Processing of Federated learning algorithm for breast cancer detection

Input: Local datasets Di = (Xi, yi) for data i, M missing, O outliers, label encoder L

Output: Federated model FL

- procedure Data Acquisition and Pre-processing
- for each data i do
- Load local dataset Di = (Xi, yi)
- Clean Di using M missing, O outliers
- Encode labels: ŷi = L(yi)
- end for
- end procedure
- procedure Local Model Training
- for each data i do
- Initialize local model: i
- Train i using CNN with Xi and ŷi
- end for
- end procedure
- procedure Model Aggregation
- Initialize federated model: M_FL
- Aggregate local models: FL = Aggregate_Models(1, 2, ..., n)
- end procedure
- procedure Global Model Training
- Compile FL with optimizer (MPA)
- Train fed using global data
- end procedure
- procedure Final Classifier
- Output: Final classifier fed
- end procedure
- Return M_FL

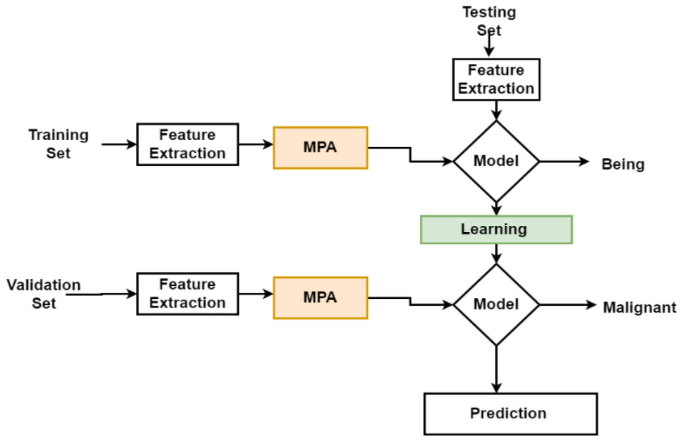

Figure 3 proposed model of breast cancer detection based on federated learning

IV. EXPERIMENTAL ANALYSIS

To evaluate the performance of the proposed algorithm for breast cancer detection and the existing algorithm for breast cancer detection, use MATLAB tools with version 2018R. The system configuration of the installed software is the operating system Windows 11, an I7 processor, and 16GB of RAM. For the validation of the algorithm employed, the image cancer dataset is CBIS-DDSM. This dataset contains sample images of the left and right breast, with a total of 2000 images. The description of the dataset is divided into different cases of cancer patients. To evaluate the performance, measure accuracy, specificity, sensitivity, and F1. The formula for parameters is given below [24.25.26].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

$$F1 = 2\,X \frac{Pricision\ X\ Recall}{Pricision + Recall} \times 100$$

TP: True Positive

TN: True Negative

FP: False Positive

FN: False Negative

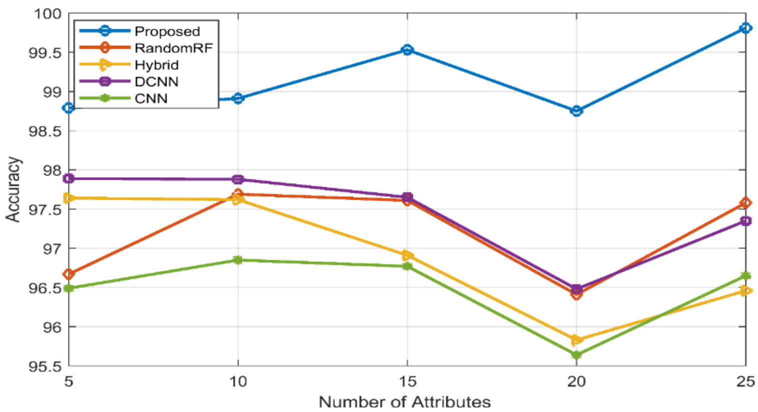

Figure: 4 Performance Analysis of Accuracy of CBIS-DDSM Dataset.

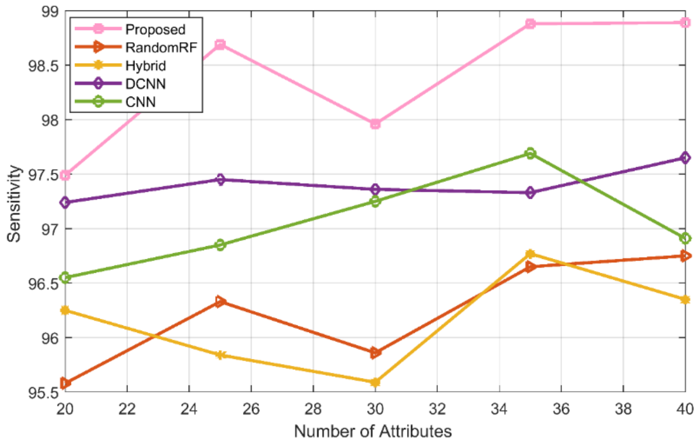

Figure: 5 Performance Analysis of Sensitivity of CBIS-DDSM Dataset.

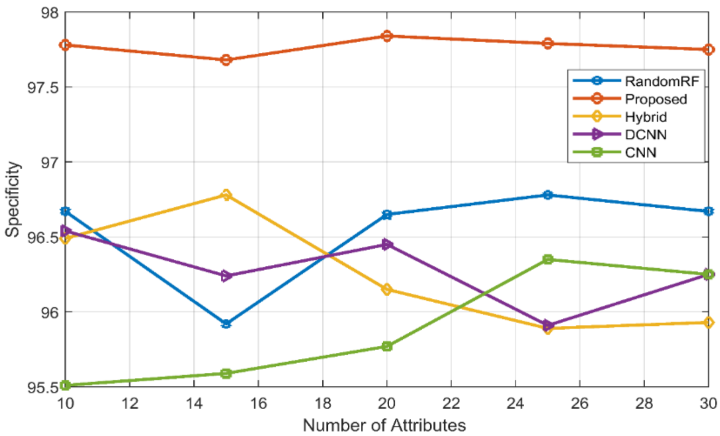

Figure: 6 Performance Analysis of Specificity of CBIS-DDSM Dataset.

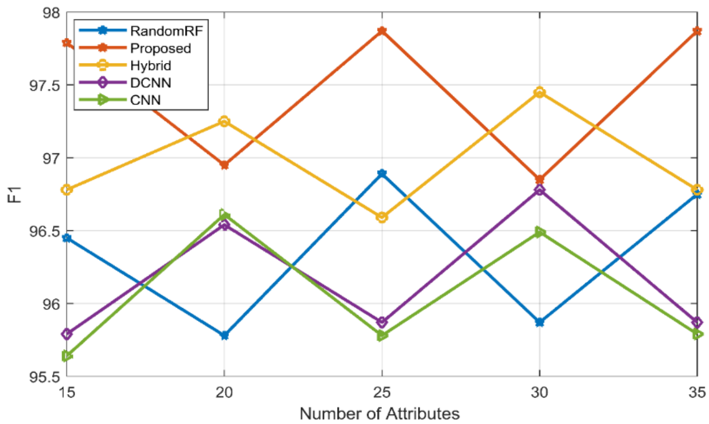

Figure: 7 Performance Analysis of F1 of CBIS-DDSM Dataset.

V. RESULT ANALYSIS

The figures (3, 5, 6, and 7) depict the iterative progression of our proposed breast cancer detection model's performance using numerical metrics, including accuracy, sensitivity, specificity, and F1-Score. Across three iterations, the figures showcase a consistent enhancement in the model's efficacy. Initially, in the first iteration, the performance indicators, such as sensitivity, specificity, and F1-Score, demonstrate relatively lower values. However, as the model undergoes refinement, particularly evident in the third iteration, there is a noticeable improvement across all these critical evaluation criteria. Of particular significance is the F1-Score, serving as a comprehensive measure of the model's overall performance. It depicts a substantial ascent from 97% in the first iteration to a robust 97.24% in the third iteration. This significant increase signifies the model's enhanced accuracy, precision, and efficiency in identifying relevant instances while minimizing false negatives. Overall, the graphical representation serves as a promising indicator of the model's potential. It vividly illustrates the model's progressive improvement, underscoring its growing effectiveness in accurately detecting breast cancer cases based on numerical data. This upward trend instills confidence in the model's ability to continually enhance its diagnostic capabilities, ultimately benefiting medical applications and patient care. The "Proposed" method consistently demonstrates high performance across various attribute sets, indicating its effectiveness in breast cancer detection. Random-RF, CNN, Hybrid, and DCNN methods are also evaluated, providing a comprehensive comparison of their accuracy, sensitivity, specificity, and F1 score. The metrics can be used to assess the trade-offs between true positives, true negatives, false positives, and false negatives for each method and attribute set, aiding in the selection of an appropriate approach for breast cancer detection based on the desired performance criteria.

VI. CONCLUSION & FUTURE WORK

Federated Learning represents a groundbreaking approach in breast cancer detection, leveraging Convolutional Neural Networks (CNNs), a common deep learning technique for biomedical image analysis. CNNs facilitate automatic feature extraction through layer-wise processing, crucial for detecting abnormalities in medical images. However, optimizing CNNs for detection tasks relies heavily on hyperparameter tuning, with each layer requiring different settings to maximize performance. Manual hyperparameter optimization is impractical due to its complexity and time-consuming nature. In response, meta-heuristic algorithms have emerged as effective tools for hyperparameter optimization across various domains. This paper introduces a novel breast cancer detection model based on federated learning, incorporating a CNN architecture and a meta-heuristic optimization algorithm, specifically the marine predator's algorithm (MPA). The MPA is utilized as the optimization algorithm, with enhancements integrated using CNN strategies to improve exploitation and prevent local optima. The proposed MPA-CNN model achieved an impressive testing accuracy of 98.32%, surpassing the performance of the traditional DCNN model, which attained a 95.95% accuracy. This highlights the significant improvement achieved by the enhanced CNN approach in optimizing hybrid hyperparameters compared to the original MPA. Additionally, the proposed approach outperformed random forest, achieving an accuracy of 98.88% compared to 95.95% for CNN. These results underscore the superiority of the proposed model compared to the four alternative algorithms considered.

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