Chapter 10
Enhancing Heart Disease Diagnosis Through Particle Swarm Optimization and Ensemble Deep Learning Models

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ABSTRACT

The present research focused on combining Particle Swarm Optimization (PSO) based hybrid deep learning models to classify heart disease images and patient sequences. This study employs Convolutional Neural Networks (CNNs), including VGG 16, VGG 19 and ResNet 50, as well as Recurrent Neu-ral Networks (RNNs), whereby their performance is optimized by PSO to im-prove the accuracy in di-

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agnosing heart disease from CT images together with associated medical history. The models experienced a significant increase in classification performance, using manual hyperparameters tuning by PSO. The combined algorithm PSO with VGG 19 and the RNN model performed best, achieving a precision of 97.78% and becoming the highest recall on testing. The model that we propose uses the modern feature extraction of VGG 19 and an RNN to take into consideration the sequential nature of data, making it very accurate while keeping loss minimal. PSO with VGG 16 and RNN model is also another robust performance with an accuracy of 94.5%.

1 INTRODUCTION

Heart disease is still one of the primary causes of illness and death in many areas around the world, highlighting a clear need for accurate and prompt diagnosis techniques. Older diagnostic methods, such as electrocardiograms (ECGs), echocardiography, and stress tests, often require expert interpretation that can have high inter-observer variability, (Krithika & Rohini, 2021) (Raja *et al*., 2021) (Swain et al., 2018). Heart disease is difficult to diagnose precisely because it involves a large number of clinical signs with subtle phenotypes. With the rapid development of medical imaging and electronic health records (EHRs), doctors benefit from these innovations, driving demands for artificial intelligence techniques to assist in disease diagnosis. In this situation, the use of machine and deep learning tools has become more popular to study large amounts of medical data that could potentially advance heart disease classification, (Pandiaraj et al., 2021) (Sharathchandra & Ram, 2022) (Deb et al., 2022).

Deep learning, a special subset of machine learning, has changed the face of medical diagnostics by producing predictive models that are able to interpret complex patterns within data. Because they are able to adaptively learn hierarchical features directly from raw pixel data, CNN have proven to be highly effective at image-based tasks. CNNs are very successful in many medical imaging tasks, such as tumor detection, organ segmentation and disease classification, (Sharma et al., 2019) (Azmi *et al*., 2022). While RNNs are great at analyzing sequential data such as medical records or time series, they are able to capture temporal dependencies and patterns over various timesteps. The combined architecture of CNNs and RNNs within a single model provides an efficient mechanism for image as well as sequential data, thereby forming a holistic approach to heart disease classification, (Gahane & Kotadi, 2022) (Sattaru *et al.,* 2022) (Sood & Mahajan, 2018) (Akter et al., 2021).

CNN, such as VGG 16, VGG 19 and ResNet50, have long been popular in medical image analysis on account of their effectiveness at learning features from high-dimensional data. VGG 16 and VGG19 — Configurations known for their extremely deep network structures, along with the use of small convolutional filters that mean feature extraction is possible at many different levels in the model, (Shyamala & Shalini, 2024) (Sarker *et al.,* 2021) (Wang *et al*., 2024). VGG 16 is a common model used for image recognition, comprising 16 layers and VGG19 with a larger convolution structure that does not miss any fine-grained detail in the images, making these models convenient to deploy for detecting abnormalities in medical CT scans, (Maurya *et al*., 2023) (Bird *et al*., 2023). Even though ResNet 50 exploits a bottleneck architecture and skips connections to resolve the vanishing gradient issue, it still allows very deep network training, which in turn boosts feature learning. While such CNN models have shown considerable improvements in the accuracy and robustness of classification, a number of challenges still exist - with overfitting and computational complexity being examples, (Sultanpure *et al*., 2024) (Chattopadhyay & Maitra, 2022).

2 LITERATURE REVIEW

RNNs are created for handling sequence type of data, remembering the previous inputs and this is useful in medical records when we have a series that spans across different timestamps. As we might be already aware, LSTM networks are a particular case of RNN, which is extensively used by medical applications as they have proved to capture long-term dependency and solve problems related to vanishing gradients. LSTMs excel at working with sequences of data (like patient histories and treatment records) to give a more holistic overview of the temporal dynamics affecting heart disease outcomes, (Wu *et al*., 2022) (Moghar & Hamiche, 2020) (Nabipour *et al*., 2020). Although RNNs and LSTM perform better in sequential data modelling, they have limitations with respect to model training and interpretation, which needs a high optimization followed by validation.

PSO (Particle Swarm Optimization) is an optimization technique based on the biological behavior of birds and fish that helps us to find the best solution in complicated search areas. It has been successfully used in the search for a good combination of hyperparameters like learning rates, batch sizes and network architectures, especially for deep learning models. This improves the performance of CNNs and RNNs in medical diagnostics by optimizing their parameters, which results in higher accuracy with better efficiency. Previous works have proven that PSO can obtain a better state of the model compared to conventional optimization techniques, so it serves as an efficient tool for fine-tuning deep learning models in medical applications, (Poh *et al.,* 2023) (Shial et al., 2022) (Laghari *et al*., 2020).

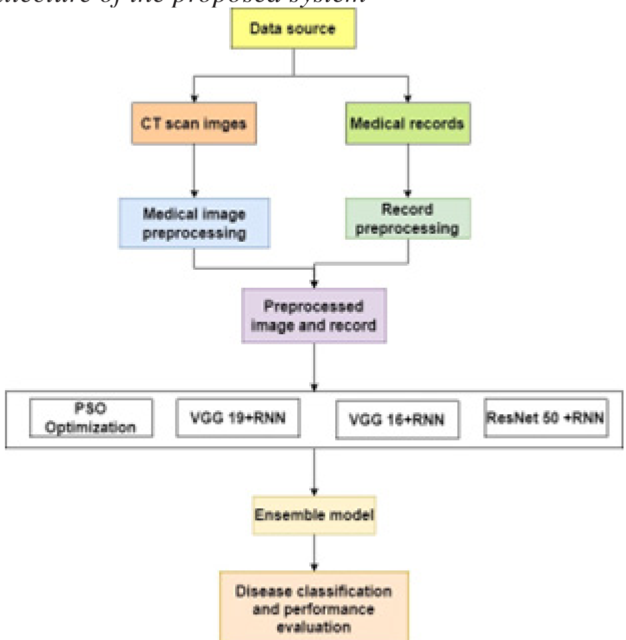
Ensemble learning is the practice of combining them together in a way that improves overall performance by increasing accuracy and helps to solve issues due to what one model missed. Display an ensemble approach for heart disease classification that combines CNNs with RNNs to take advantage of both image-based and sequential data. This can be done for classification by combining predictions from multiple models to make stacking, averaging or weighted voting (such as Bagging and Boosting) set Enabled which provides more robustness in prediction along with accuracy. Since CNNs such as VGG 16 or VGG 19 are efficient in processing CT scan images and RNNs can dynamically model the diagnosis history described by medical records, we combined them together for a more comprehensive analysis, which could improve the predictive capabilities of our classification system. There is much empirical evidence for the successful application of ensemble methods that improve classification accuracy and generalization in the previous research, (Olowookere & Adewale, 2020) (Turk et al., 2022) (Talebizadeh & Morindnejad, 2011).

The reviewed literature discusses the developments in deep learning models, such as CNNs and RNNs, used for heart disease classification. Since CNNs are strong in analyzing images and RNNs for sequential data analytics, one can conclude that combining these models is possible due to their complementary characteristics. Particle Swarm Optimization provides an effective combination for both optimization of deep learning models and ensemble method, but few studies have been conducted on solving this problem in the context of heart disease classification. The goal of this study is to fill in the gap by incorporating PSO with different CNN and RNN models and then applying the ensemble method for improved classification performance. The results offer critical information for enhancing and synergizing deep learning approaches to improve heart disease detection outcomes.

3 METHODOLOGY

This research uses a nature-inspired optimization algorithm called PSO to accelerate the deep learning models in heart disease classification. The methodology of the research is shown in figure 1. The method imputes the well of creating more accurate and reliable diagnoses via tuning their hyperparameters using PSO into Convolutional Neural Networks (CNNs) and Recurrent Neural Networks(RNN). PSO is inspired by the social behavior of birds flocking or fish schooling to do random walks over many hyperparameter combinations. Each particle in the swarm is a potential solution, and it has different combinations of learning rates, layer structures and other hyperparameters. These particles move through the solution space and adjust their positions based on the collective experience of the swarm to converge iteratively to an optimal set of hyperparameters that give rise to the highest model performance.

Figure 1. Architecture of the proposed system



CNN models such as VGG 16, 19 and ResNet50 are used for image-based analysis due to their skill in hierarchically extracting features from medical images like CT scans. Also, when we integrate the PSO optimization with these models, it would become much more efficient in tuning hyperparameters, which improves the performance of both the feature extraction process and classification accuracy for those state-of-the-art image classifications. PSO is used to optimize parameters including filter number, kernel size, learning rate and structure of fully connected layers, which play an important role in the ability of the CNN to detect heart organ abnormality through CT scan image correctly.

Meanwhile, RNN models are used to analyze medical records as a sequence of events that is important for learning the temporal relationships occurring in patient health record data. More broadly, RNN models are very good at dealing with data that come in a sequence; they are useful for looking across ECG, patient history and other time-based reports. To make sure that the model is able to capture a complex dependence on time, the PSO algorithm towards fine tuning of hyperparameters pertaining to a number of recurrent units and choice of activation functions specific to RNNs are employed.

These predicted outputs of the optimized CNN and RNN models are later fused in this research to present a total decision on the heart health of an individual. The coordinated model makes a more accurate prediction about coronary artery disease by combining image analysis and sequential data processing. The aggregate methodology leverages the CNN for visual data analysis and the RNN is excellent at handling sequential records, with PSO providing optimal hyperparameter adjustments to each model.

3.1 Particle Swarm Optimization

PSO is a powerful computational technique that originates from the social behavior of animals, such as birds flocking or fish schooling. It is employed to solve an optimization problem by generating the candidate solution and iteratively improving it with respect to a quality measure, which needs to be defined finally called the fitness function. PSO attempts to achieve the best performance on heart disease classification by searching for and selecting parameters having optimal values.

PSO works by starting with a swarm of particles, where each particle denotes an assigned solution in hyper-parameter space. Each particle has a position that maps to some hyperparameters and the complete experience of each swarm causes each individual particle to move all throughout this space. In mathematical form, the position of a particle xi(t) at time t is updated according to its velocity vi(t), which in turn depends on two influences: Its personal best pi(t) and the global best g(t). The velocity equation of the PSO is given by:

$$v_i(\mathrm{t}+1) = \omega\, \mathrm{v}_i(t) + \mathrm{c}_1 r_1 \left(p_i(t) - \mathrm{x}_i(t)\right) + \mathrm{c}_2 r_2 \left(g(t) - \mathrm{x}_i(t)\right) \tag{1}$$

where ω is the inertia weight to modify the influence of previous velocity, c_1 and c_2 are cognitive social coefficients that can be used as weights that tune how much we use personal global best positions, respectively. The

r_1 and r_2 are random variables. The new position of a particle can be updated as:

$$x_i(\mathrm{t}+1) = \mathrm{x}_i(t) + \mathrm{v}_i(\mathrm{t}+1) \tag{2}$$

This process is iterative and continues until the swarm converges to a solution optimal for hyperparameter tuning, which would be the parameters that give your deep learning model its best performance.

The great simplicity of PSO is the effective search that can handle large search spaces efficiently. Its effectiveness lies in the trade-off between exploration (seeking out new areas) and exploitation (refining solutions known to be good). In this research, PSO is used to hyperparameter tuning CNN and RNN models in heart disease classification so that the model is fine-tuned for accuracy, improving the overall correctness of the diagnostic system.

3.2 Preprocessing of Dataset

The success rate of heart disease classification with a deep learning model completely depends on the data preprocessing that we did before training. The first collection is of two sizes. Medical images have detailed types, such as CT scans, and the second is structured and duplicated from health-related tracks. Each of the datasets will be pre-processed differently to suit input into Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN).

In image acquisition and normalization, preprocessing starts with the CT scan images. Images may have different sizes and resolutions, so we need to resize the images into one fixed dimension for us to feed them in CNN Models such as VGG 16, VGG19, and ResNet50. Usually, the images are reduced to 224x224 pixels which is a common input size for those CNN architectures. This resizing is critical because it enables the models to work with these images as input data without losing enough of their important structural properties that would be necessary for accurate classification. Both large-size and small-size images are normalized to [0, 1] directly after resizing. This step is important because it helps speed up the convergence of the training process by making sure that feature-wise values have similar scales so one range of pixel sizes does not bias the model.

Data augmentation techniques are also utilized to improve the generalization capability of CNN models. The process of data augmentation is responsible for generating more training samples by applying random rotations, translations, flips and zooms to original images. This technique is designed to make the model generalize better by imaging a heart at various potential distortions and orientations under CT towards what might be encountered in reality. This makes the model generalize better because of increased variety, which means less overfitting and more accurately classifying blind images.

Preprocessing the sequential medical records, which includes heterogeneous datatypes and temporal sequences. Before training the model, EMR data including patient history and other time-dependent clinical measurements — must be first cleaned to eliminate inconsistencies and missing values. Where missing data is found, methods like forward fill, and interpolation are applied to estimate and impute the gaps so that sequences remain contiguous and coherent. During normalization, all the aggregated data is brought onto a universal scale (min-max scaling or z-score normalization). For RNNs specifically, this really enables the model not to be dominated by features with larger numerical ranges.

Then, this sequential data is altered to fit into the required input format of an RNN once it has been normalized. This requires shaping the data into time steps, where each bundle of sequences is an individual patient's medical history signal. Padding is used to increase the length of all sequences; therefore, having uniform input sizes allows us to create batches more efficiently. In addition, techniques like one-hot encoding are utilized to convert categorical variables in medical records, such as diagnosis codes or medication types, into numerical formats that an RNN could understand.

Then, the image and sequential datasets are divided into training, validation, and test sets. We will use the training set to fit the models, and we are going to create another validation data during the PSO process for tuning hyperparameters. The test set is used to check how the final model performs, and that other data can be properly generalized.

This study has conducted the training and testing of deep learning models using a dataset, which is obtained based on a number of 2,300 records. To ensure a balanced evaluation, we give 70% of the data (1610 records) for testing. It allows us to test the generalization ability of our models on large unseen data. The remaining 30%, or 690 records, are employed to train the models where hyperparameter tuning and model understandings of underlying patterns in data occur.

3.3 Deep Learning Model

This research implemented deep learning (DL) based models to recognize heart diseases in medical images and records using biomedical imaging alongside the CNNs, namely VGG 16, VGG 19, and ResNet50 for image processing, followed by Recurrent Neural Networks. These models are catered to handle specific kinds of data based on their structure and the limitations they have, using these constraints as advantageous for the classification process.

VGG 16 and VGG 19 are deep CNN models known for their simplicity and effectiveness in image classification tasks. Both models consist of multiple convolutional layers followed by fully connected layers, which are designed to automatically learn hierarchical features from the input images. In these models, the convolution operation is mathematically defined as:

$$y_{i,j,k} = \sum_{m.n.l} x_i + m, j + n, l \,.\, w_{m,n,l,k} + b_k \tag{3}$$

The variables $y_{\mathrm{i,j,k}}$ are the pixel values of the input image at a position, $w_{\mathrm{m,n,l,k}}$ is the convolutional filter weights, and bk is the bias term. For the VGG models, a stack of convolution layers (typically 33×3 filters) is followed by two fully connected layers, which enable them to learn higher-level features. After each convolutional layer, we apply ReLU (Rectified Linear Unit) activation functions, which bring the non-linearity in our CNN, helping it to learn more complex patterns. The equation gives the ReLU function:

$$f(x)=\max(0,x) \tag{4}$$

Another CNN used in this research is ResNet 50 (which introduces a key innovation with its residual learning framework). ResNet 50 uses skip connections, not in normal CNNs and the function is added to the original input. This solution solves the vanishing gradient problem and makes it possible to train very deep networks. Generally, ResNet is about one main concept the residual block defined as:

$$y=F(x,\{Wi\})+x \tag{5}$$

$F(x,\{Wi\})$ stands for the residual mapping to be learned at a few stacked layers, which are multiplicative with weights Wi, and x denotes identity mapping added directly. This addition allows the gradient to directly pass through without vanishing, thus making deeper model training easier. ResNet 50 contains a total of 50 layers with a lot of residual blocks, making it very convenient to learn features when dealing with complex image classifications such as heart disease diagnoses from CT scans.

Recurrent neural networks (RNNs) are used to analyze sequential medical records of a patient. In literature examples, short-term memory Networks model temporal dependencies in the data patient history or ECG readings. RNNs are different from feedforward networks in that they have connections forming a directed cycle meaning it allows the node to keep a hidden state which is able to store some of the information seen during earlier time steps. In an RNN, the hidden state ht at time *t*

is calculated by:

$$ht=\tanh(Wh\times ht\text{-}1+Wx\times xt+bh) \tag{6}$$

Wh and Wx are the weight matrices for the hidden state, input respectively; xt is the t-th time step given as input. The bias term b. This is done by using the tanh function, which acts as our activation function in order to introduce non-linearity. RNNs excel at sequence-related tasks by modelling the relationship in time series data that are prevalent among various medical records, where the order and timing of activities are cardinal.

However, traditional RNNs face problems like vanishing gradients when dealing with long-term dependencies. More advanced variants, such as Long Short-Term Memory (LSTM) networks, are addressed to combat this, which utilize gating mechanisms enabling it to keep track of important things along the series. The LSTM architecture uses input, forget and output gates that control when information passes through (or is forgotten by) the network in order to remember important details well over long sequences.

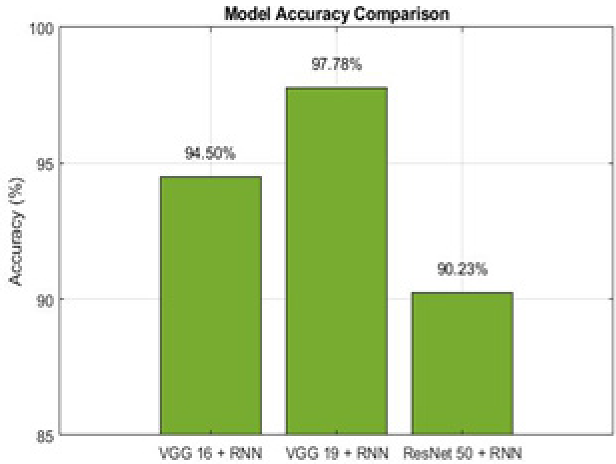
This research uses the concatenation of these models, namely VGG 16 and VGG 19, for image analysis along with ResNet 50 and LSTMs in RNNs as well (for sequential medical record datasets) to achieve a complete heart disease classification system. PSO technique is employed for tuning each model to improve the system performance, where it becomes a sustainable, non-invasive surgical tool in diagnosing heart disease using complex medical data.

4 RESULT AND DISCUSSION

After having trained the models, during testing it is seen that using Particle Swarm Optimization (PSO) with VGG 16 and Recurrent Neural Network (RNN), heart disease can be predicted at an accuracy of around 94.5%. High precision proved the power of combining CNN for analyzing fine-grained visual features from CT scan images and RNN capable of capturing temporal dependencies in medical records. The PSO optimization, as the main point of the fine-tuning process for hyperparameters in both models, has a relevant role in achieving an efficient predictive method by combining them. The result of accuracy is shown in Figure 2.

However, if PSO is combined together with VGG 19 and RNN the accuracy increases more than this step to reach 97.78%. Due to the higher depth of this architecture, the VGG 19 model is able to get richer features from images, and therefore, when combined with sequential analysis power, RNN networks will show better performance. This ensemble achieves the highest accuracy in all models tested because PSO balances effectively optimizing hyperparameters.

Figure 2. Accuracy of each model



Deep Learning using the models PSO with ResNet 50 and RNN achieved a correct prediction accuracy of about 90.23%. Combined, this gives the model slightly lower capability than its counterparts. Although ResNet 50 with residual learning architecture captures more complex patterns in images and, used together with RNN optimized by PSO, presents a robust prediction model for heart disease classification, the accuracy is slightly lower than VGG-based models.

Figure 3 presents the summary of the three combinations of the deep learning models; PSO with VGG 16 and RNN, PSO with VGG 19 and RNN, and PSO with ResNet 50 and RNN identifying heart disease. Technical-wise, the performance of a model is assessed based on four criteria precision, recall, F1 score, and accuracy. According to the findings, the PSO with VGG 16 and RNN has a precision of 0.92, recall of 0.95, F1 score of 0.94, and accuracy of 94.50%. Overall, this model is highly effective at identifying cases of heart disease measured against the balance between precision and recall as applied by the F1 score. The PSO with VGG 19 and RNN prove to be superior to the other two, having a precision of 0.98, recall of 0.97, F1 score of 0.98, and accuracy of 97.78%. Such results show that the model is highly reliable for classifying cases of heart disease. Lastly, the PSO with ResNet 50 and RNN model has a region of 0.89, recall of 0.91, F1 score of 0.90, and accuracy of 90.23%. Although slightly lagging behind, the performance of the other models from the combination offers reliable predictions establishing the effectiveness of the deep residual learning of ResNet 50 together with RNN in medical record analysis.

Figure 3. Performance score of each model

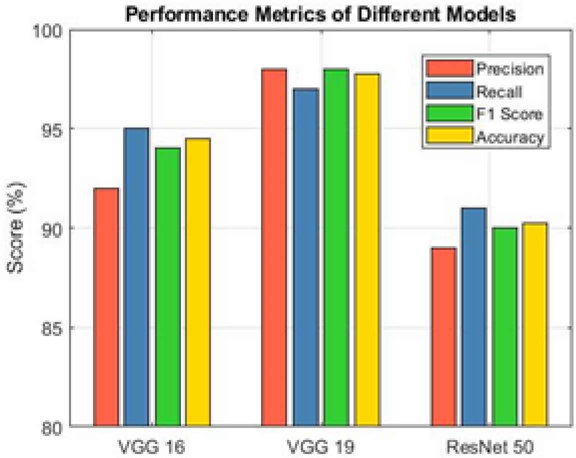


Figure 4 are the confusion matrices of PSO-VGG16 RNN and PSO-VGG19 RNN and ascribes to their performance. The confusion matrix of the PSO with VGG 16 and RNN model for true positive (TP) = 453, false negative (FN) = 24, false-positive (FP) = 31true-negative (TN) = 1492. This says that the model is good, but there is some false classification. The PSO with VGG 19 and RNN model shows the best results of all models, where there are 481 TP and 11 FN. The number of False Positives (FP) is also lower than other models at only 18 FP, while TN has a maximum value=1490 showing high accuracy and making few missed classifications compared to other configurations.

The PSO with ResNet 50 and RNN model is given by the number of TP = 422, FN = 39, FP = 50, TN = 1,482, which indicates that this best-performing models have good performance but relatively has a greater number of false negatives and fake positives as to those in VGG based models. Overall, using confusion matrices and performance metrics, PSO with VGG 19 + RNN model is the better one out of all as far as accuracy and F1 score are considered, which gives more accurate heart disease classification with lesser error.

Figure 4. Confusion matrices

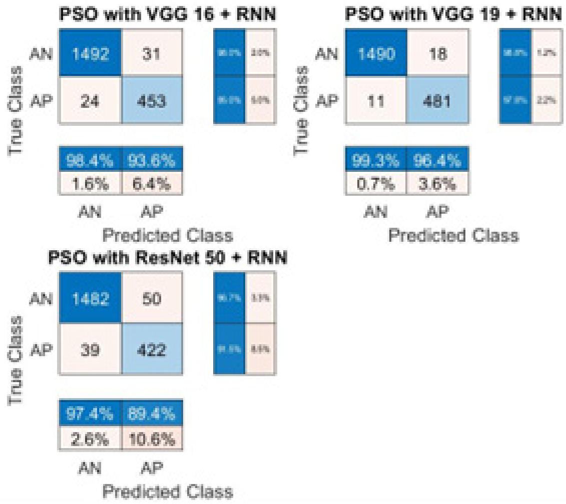
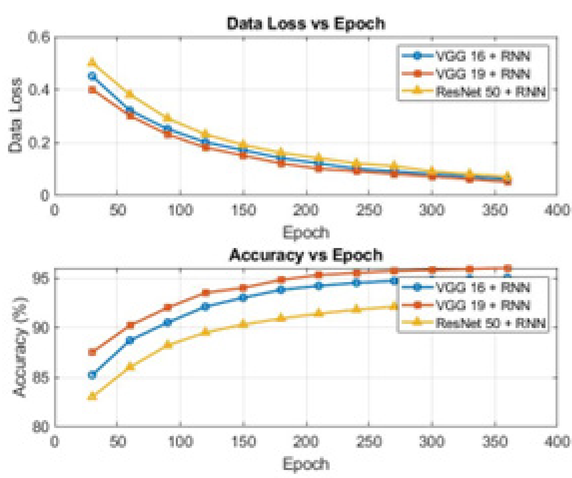


Figure 5 shows the data metrics: data loss and accuracy expressed in percentage for different epochs for the three model combinations PSO with VGG 16 and RNN, PSO with VGG 19 and RNN, and PSO with ResNet 50 and RNN. Firstly, in PSO with VGG 16 and RNN from 30 epochs, data loss of 0.45 has to decline up to 0.06 in 360 epochs, and accuracy rises from 85.2% to 95.0% from the given perspective over the training period. Therefore, the model has been able to minimize loss and, at the same time, improve accuracy.

Figure 5. Data loss and epoch of each model



For PSO applied to VGG 19+RNN, the data loss with the same training set decreased from about 0.40 at 30 epochs down to approximately 0.05 after 360 generations, and accuracy rose from 88% to 96%. This model shows better performance than VGG 16 since its accuracy and loss improvement are faster (logarithm plot scale), which in terms easier for learning from the data.

Data loss improves from 0.50 to just 0.07 (360 epochs) in PSO with ResNet-50 and RNN, where accuracy is changed from a static range of 83%–90% on the same number of epochs reached. Although it indicates consistent improvement, its accuracy is slightly lower than that of the VGG-based models. In conclusion, PSO combined with VGG 19 and RNN achieves the highest accuracy but lowest data loss in all models.

5 CONCLUSION

In this research, the combination of PSO and deep learning models is applied for prediction accuracy in heart disease. Through PSO complexed with Convolutional Neural Networks (CNNs) such as VGG 16, VGG 19 and ResNet-50 that are associated with Recurrent Neural Network RNNs, important improvements have been obtained in the predictive results. The combined model of PSO, VGG 19 and RNN has the upper hand over all the models, giving an accuracy of 97.78% with very little data loss up to a high precision, recall rate and F1 score. This model incorporates the powerful feature extraction capabilities of VGG 19 with depth and sequential analysis strengths of RNNs using PSO for getting even better classification results. Likewise, PSO with VGG 16 and RNN are optimal, achieving an accuracy of approximately 94.5%, while PSO with ResNet 50 Perform with an accuracy of 90.23% is the best performance but a little less than others due to lack of the optimized model. These results present the importance of proper hyperparameter finetuning in achieving good performance on a model. The proposed ensemble method that combines the analysis of image-based and sequential data, clearly shows a generalizable pattern for disease diagnosis. The study demonstrates the promise of state-of-the-art deep learning methods and optimization strategies for medical diagnostics and also underscores that enhanced manifold modelling appears useful in handling multi-label classification challenges.

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