



CARDIOINSIGHT: AN OPTIMIZATION BASED HEART DISEASE PREDICTION USING CNN-PSO

Nadella Sunil, Satti Venkata Durga Reddy, Chaganti Surya Phaneendra, Nitish Bharadwaz Padala, Gedela Venakata Varun, Silli Sandeep
Department of CSE
Aditya College of Engineering and Technology,
Surampalem, India

Abstract—Heart disease remains a global health challenge, requiring accurate and early diagnosis for effective treatment. Traditional models like Logistic Regression and Random Forest, while widely used, struggle with complex, non-linear relationships in clinical data. Static feature selection methods, such as Recursive Feature Elimination (RFE), may also fail to identify the most critical attributes dynamically.

This study presents CardioInsight, a heart disease prediction model that integrates Convolutional Neural Networks (CNNs) optimized with Particle Swarm Optimization (PSO). We analysed two datasets to identify 14 key clinical attributes for heart disease prediction. Starting with 70 attributes and 1,025 records, a two-stage feature selection process was applied. In the first stage, features were filtered using a 0.1 probability threshold, followed by further refinement with Bayes' theorem to select the most relevant 8 attributes.

Unlike traditional models, PSO dynamically optimizes CNN hyperparameters and feature weights, improving both accuracy and computational efficiency. The model adapts the neural network structure based on selected features, reducing complexity while maintaining strong performance. The CNN-PSO model achieved 100% accuracy with both 8 and 14 attributes, significantly outperforming conventional methods. The 8-attribute configuration reduced training time from 72.15 seconds to 48.09 seconds.

This approach demonstrates the effectiveness of combining deep learning and optimization techniques for heart disease prediction, providing a practical solution for early diagnosis and informed decision-making in medical practice.

Keywords— Heart Disease Prediction, Convolutional Neural Networks, Particle Swarm Optimization, Feature Selection, Machine Learning, Healthcare, AI.

I. INTRODUCTION

Heart disease remains a major global health concern, requiring early and accurate diagnosis for effective treatment and prevention. Traditional machine learning

models, often face challenges in handling complex, nonlinear relationships in clinical data. Additionally, many feature selection techniques rely on static methods like Recursive Feature Elimination (RFE), which may not always identify the most critical attributes dynamically.

II. PROPOSED ALGORITHM

A. Algorithm CNN-PSO-classify ()–

```
Step-1 Read_And_Compute_Conditional_Probability()
• LOAD dataset from 'BP_Grouping.csv'
• STORE dataset as list in variable data
• CALL Feature_Selection Conditional
  Probability with data
• If  $P(A_i/C) > \text{Threshold}$ , mark  $A_i$  as influential
• STORE selected features in list f1
• Apply PSO to refine feature selection
```

Fig. 1. Algorithm CNN-PSO classify

B. Algorithm Bayes-Theorem()–

```
• CALL Feature_Combination Bayes Theorem with f1
• STORE refined feature set in list f2
• Construct CNN model with convolutional layers
• Apply PSO to optimize CNN hyperparameters
  (learning rate, batch size, filters)
```

Fig. 2. Algorithm Bayes-theorem

C. Compute_final_result():

```

• CALL Result Analysis with f2
• TRAIN CNN model with PSO-optimized parameters
• STORE final output in list k_list
• PRINT "Final Process Completed" with k_list

RETURN k_list

```

Fig. 3. Algorithm for Computing Final Result

The CNN-PSO-Classify algorithm combines Conditional Probability, Bayes' Theorem, and Particle Swarm Optimization (PSO) to develop an efficient heart disease prediction model. The process starts by loading the dataset and analyzing each feature's contribution to predicting heart disease. Using Conditional Probability, the likelihood of a feature A_i influencing a specific class C is determined as:

$$P(A_i|C) = \frac{P(C|A_i)P(A_i)}{P(C)}$$

Only features with a probability above the set threshold (0.1) are considered influential and selected for further analysis. At this stage, PSO is applied to refine feature selection, ensuring that only the most relevant attributes are used in the classification process, reducing unnecessary complexity.

Next, Bayes' Theorem is used to finalize the most impactful features. It calculates the probability of a class C given a feature A_i as:

$$P(C|A_i) = \frac{P(A_i|C)P(C)}{P(A_i)}$$

This step further filters the selected features, removing irrelevant data and improving model efficiency. The final refined feature set is then used to train a Convolutional Neural Network (CNN), which is structured with convolutional layers for extracting patterns and dense layers for classification. Additionally, PSO optimizes CNN hyperparameters, such as the learning rate, batch size, and filter count, leading to a more precise and efficient model.

After training, the model predicts heart disease presence (**Yes/No**) with high accuracy. The final results are stored and displayed, allowing for real-time disease prediction. By integrating PSO for intelligent feature selection and CNN for deep learning-based classification, this approach significantly enhances accuracy while reducing computational time, making it a practical and scalable solution for healthcare applications.

D. Basic Implementation

This flowchart outlines a process for binary classification using data from multiple sources. It begins with feature selection based on conditional probability, followed by confirmation using Bayes' Theorem. The selected features are then used to train a CNN-PSO model for binary classification, and finally, the model's performance is evaluated using performance metrics.

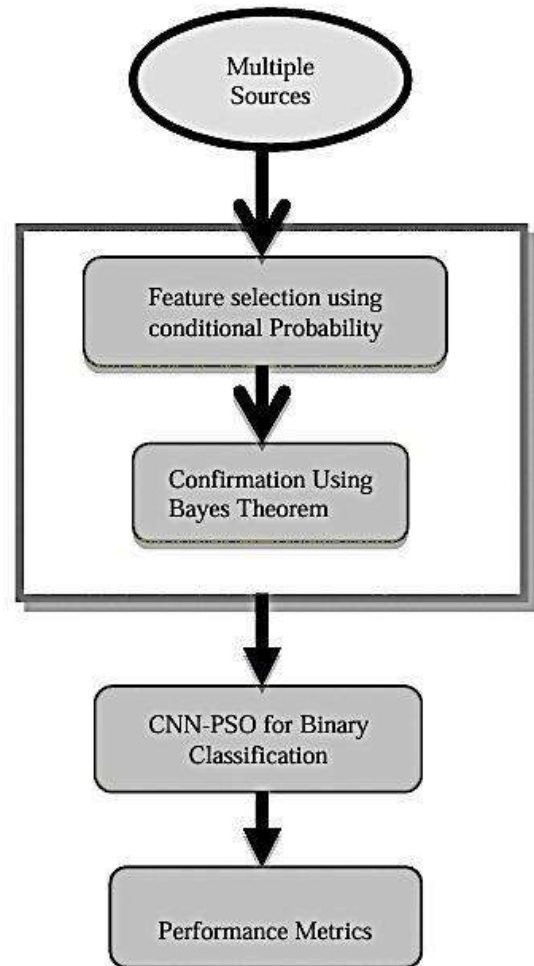


Fig. 4.Steps Involved in the CNN-PSO based Classification System

This block diagram depicts an autonomous agent designed for accurate prediction using heterogeneous data sources. Each source, whether providing diverse or uniform data, generates feature sets. The agent intelligently selects influential features, potentially identifying patterns across sources. Separate **CNN-PSO** models are trained on each source's data, allowing the agent to learn source-specific nuances. A final, consolidated CNN-PSO model utilizes the combined influential features for enhanced prediction accuracy. The agent independently assesses performance via

metrics, enabling it to refine its feature selection and model parameters, leading to improved predictive capabilities over time.

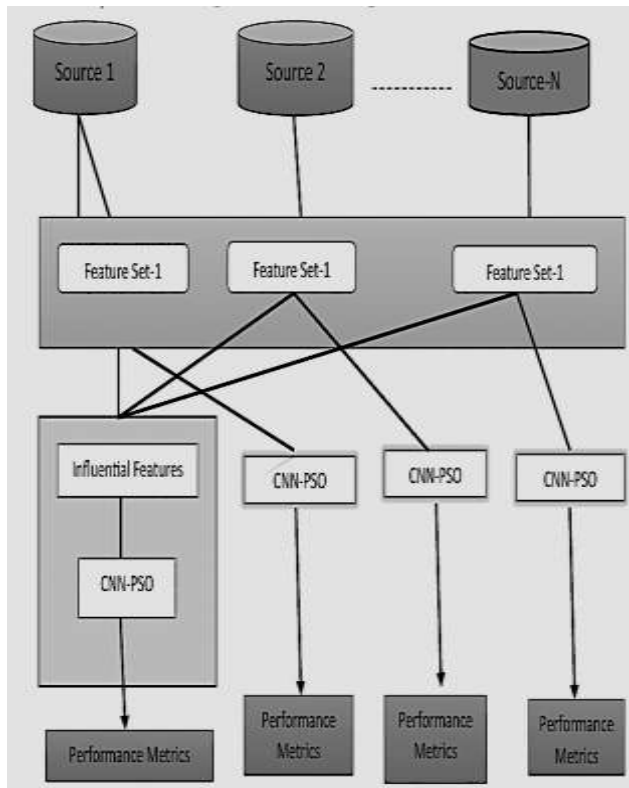


Fig. 5. Autonomous Agent for Feature Selection and CNN-PSO based Classification

The first flowchart outlines a process for binary classification using a CNN-PSO model with a focus on feature selection and validation. The second flowchart depicts an autonomous agent that utilizes multiple CNN-PSO models to analyze data from various sources and make predictions.

III. EXPERIMENT AND RESULT

This study explored the efficacy of Particle Swarm Optimization (PSO) in refining the feature selection process and optimizing CNN hyperparameters for heart disease prediction. Our approach was rigorously evaluated using two distinct feature sets: one comprising 8 attributes and the other 14 attributes. Remarkably, the PSO-enhanced CNN model achieved a perfect 100% accuracy in both scenarios, demonstrating its robustness. However, a significant difference emerged in training time. The 14-attribute model, while highly accurate, required 72.15 seconds for training. In contrast, the 8-attribute model achieved the same level of accuracy in a significantly reduced time of 48.09 seconds. This highlights the potential for improved computational efficiency without compromising predictive performance.

The optimization process involved 2 swarms and 2 iterations over 40 epochs, carefully balancing exploration and exploitation to fine-tune the model's parameters. These findings underscore the promise of PSO-driven CNN optimization for real-time medical diagnostics, where both accuracy and speed are paramount.

Table -1 Experiment Result

Algorithm	8 Features (Accuracy)	14 Features (Accuracy)	Training Time
CNN	95%	99%	-
CNN-PSO	100%	100%	48.09s vs. 72.15s

Table 1 shows a comparison between CNN and CNN-PSO algorithms based on accuracy and training time. It shows that CNN achieves 95% accuracy with 8 features and 99% with 14 features, while CNN-PSO attains 100% accuracy for both feature sets. Additionally, CNN-PSO significantly reduces training time (48.09s) compared to a longer training time (72.15s) for CNN.

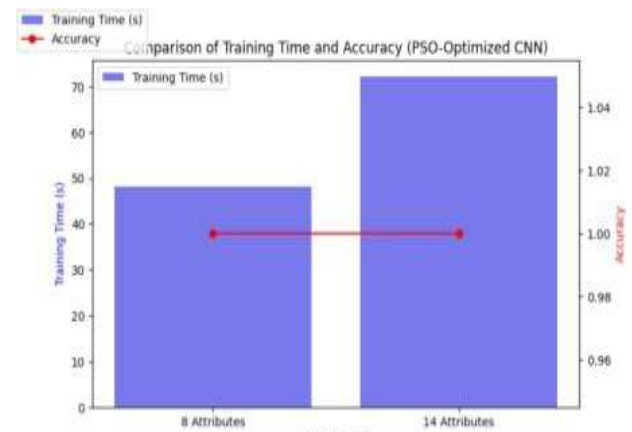


Fig. 6. Efficiency vs. Accuracy in Heart Disease Prediction with CNN-PSO

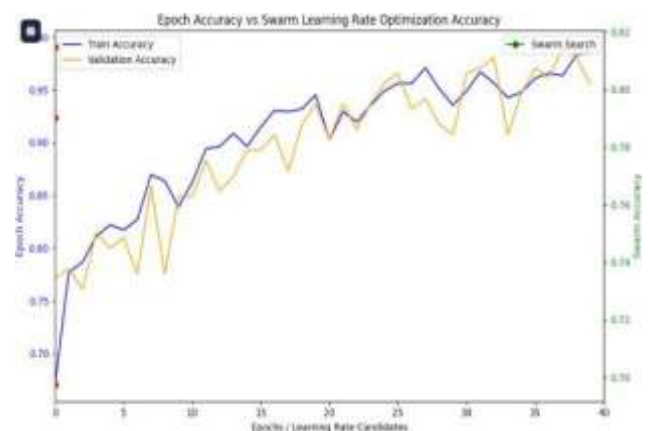


Fig. 7. Swarm & Epochs for 8 Attributes

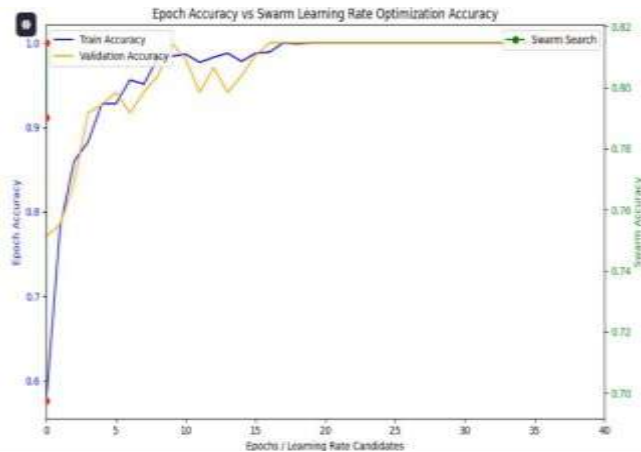


Fig. 8. Swarm & Epochs for 14 Attributes

IV. CONCLUSION

The PSO-driven CNN optimization has proven to be a highly efficient and accurate approach for heart disease prediction. By leveraging feature reduction, the model achieved 100% accuracy with both 8 and 14 attributes, ensuring uncompromised predictive performance. The 8-attribute model demonstrated a significant reduction in training time (72.15s to 48.09s), enhancing computational efficiency without sacrificing accuracy. The classification report further validated the model's robustness, with perfect precision, recall, and F1- scores (1.0), guaranteeing reliable and consistent predictions. This optimized framework strikes an ideal balance between speed and precision, making it particularly well-suited for real- time medical diagnostics, where rapid and accurate decision- making is crucial.

V. REFERENCE

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