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[1] D. Cenitta
[2] R. Vijaya Arjunan*
[3] Krishnaraj Chadaga

# Hybrid Deep Learning and Squirrel Search Algorithm for Early Prediction of Heart Disease with IoT-Integrated Health Monitoring Systems

***Abstract: -*** This research proposes a hybrid approach combining deep learning models with the Squirrel Search Algorithm (SSA) for early heart disease prediction. Integrating Internet of Things (IoT) devices for real-time health monitoring enhances predictive capability and provides continuous patient data. The proposed model optimizes feature selection using SSA, ensuring that the most relevant and impactful features are used for prediction, which improves the accuracy and efficiency of the deep learning models. This study aims to provide a robust, real-time heart disease prediction system that can be seamlessly integrated into modern healthcare infrastructures.

***Keywords:*** Heart Disease Prediction, Deep Learning, Squirrel Search Algorithm, Feature Selection, IoT, Real-Time Monitoring, Healthcare Technology.

## I. Introduction

Heart disease continues to rank among the world's leading causes of death, taking millions of lives annually. To effectively manage and treat patients, early detection and ongoing monitoring are essential as they greatly lower the likelihood of poor consequences. Conventional techniques for predicting cardiac disease frequently depend on manual analysis and static clinical data, which can be laborious and error prone. Consequently, there is a pressing need for more efficient, accurate, and real-time predictive systems that leverage advanced computational techniques and modern technology [1]. The advent of deep learning has revolutionized various domains, including healthcare. DL models, particularly NN, have demonstrated exceptional performance in pattern recognition and predictive analytics. These models can analyze complex, high-dimensional medical data to identify subtle patterns indicative of heart disease. However, the effectiveness of deep learning models largely depends on the quality and relevance of the input features [2]. Feature selection becomes a critical step in the modelling process, as it ensures that only the most informative and impactful features are used for prediction. The Squirrel Search Algorithm (SSA) is a novel nature-inspired optimization technique based on the foraging behavior of squirrels. SSA has shown promise in various optimization problems due to its ability to efficiently explore and exploit the search space. By mimicking the dynamic and adaptive foraging strategies of squirrels, SSA can effectively identify optimal feature subsets from large datasets. This optimization capability makes SSA an excellent candidate for enhancing the feature selection process in heart disease prediction models [3]. In parallel with advancements in computational methods, the integration of Internet of Things (IoT) devices into healthcare systems has opened new avenues for real-time patient monitoring. IoT devices, such as wearable sensors and smart health monitors, continuously collect and transmit physiological data, providing a rich source of real-time information. This continuous data stream enables timely detection of abnormalities and facilitates proactive health management. By integrating IoT with predictive analytics, healthcare providers can achieve a more holistic and responsive approach to patient care [4].

This research proposes a hybrid approach that combines deep learning models with the Squirrel Search Algorithm (SSA) for early heart disease prediction, enhanced by IoT-integrated health monitoring systems. The primary objective is to develop a robust and accurate prediction model that can operate in real-time, leveraging continuous data from IoT devices and optimized feature selection through SSA [5]. This hybrid model aims to address the limitations of traditional prediction methods by improving accuracy, reducing false positives and negatives, and providing a seamless integration into modern healthcare infrastructures. The global burden of heart

[1] Department of Computer Science and Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education (MAHE), Manipal, Karnataka 576104, India. cenitta.d@manipal.edu

[2] Department of Computer Science and Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education (MAHE), Manipal, Karnataka 576104, India.

[3] Department of Computer Science and Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education (MAHE), Manipal, Karnataka 576104, India. krishnaraj.chadaga@manipal.edu

*Corresponding Author: [2]R.Vijaya Arjunan* (vijay.arjun@manipal.edu)

disease underscores the importance of innovative predictive methods. Cardiovascular diseases, including coronary artery disease, heart failure, and arrhythmias, often present with subtle and non-specific symptoms that can easily be overlooked. Early intervention is critical for preventing disease progression and improving patient outcomes. Traditional diagnostic methods, such as electrocardiograms (ECGs) and echocardiograms, while effective, are often limited by their reliance on episodic testing and manual interpretation [6].

Deep learning and machine learning have lately become popular methods for diagnosing medical conditions. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are deep learning models that have been effectively used with a variety of medical imaging and time-series data [7]. These models can automatically extract relevant features and identify complex patterns that may not be apparent to human observers. However, the performance of these models is heavily dependent on the selection of input features, which can be a challenging task given the high dimensionality and heterogeneity of medical data [8]. To tackle this problem, feature selection techniques have been applied, including genetic algorithms, particle swarm optimization, and ant colony optimization. The Squirrel Search Algorithm (SSA) adds to this repertoire with its unique approach inspired by the dynamic foraging behavior of squirrels. SSA's ability to adaptively search for optimal solutions makes it particularly suitable for feature selection in large and complex datasets [9].

IoT technology has enabled continuous and remote patient monitoring, further revolutionizing the healthcare industry. Heart rate, blood pressure, and activity levels are just a few of the physiological indicators that wearable technology, such as smartwatches and fitness trackers, can measure [10]. Large volumes of data are produced by these devices, and real-time analysis of the data can be used to identify early indicators of cardiac disease. Predictive algorithms that include Internet of Things data have a great deal of promise to increase the precision and promptness of cardiac disease diagnosis. In conclusion, the combination of deep learning, SSA-based feature selection, and IoT-enabled monitoring presents a promising approach for early heart disease prediction. This hybrid model aims to enhance predictive accuracy and provide real-time insights, ultimately contributing to better patient outcomes and more efficient healthcare delivery. The following sections will detail the proposed system's methodology, implementation, and evaluation, highlighting its potential to revolutionize heart disease management [11].

## II. Related Works

Using a variety of machine learning (ML) and deep learning (DL) techniques, the identification and diagnosis of ischemic heart disease (IHD) have been actively researched. This section examines current developments in machine learning (ML) models, feature selection algorithms, and Internet of Things (IoT) device integration in the healthcare industry, with an emphasis on their applications to IHD prediction. The discussion includes the limitations of current approaches and highlights the potential improvements introduced by the Squirrel Search Algorithm (SSA) and its variants. Machine learning has completely changed the way that heart disease is diagnosed, according to Cortes et al. [12]. Because they are easy to understand and straightforward, traditional techniques like logistic regression and decision trees have found widespread application. However, the complexity and high dimensionality of medical data frequently pose challenges for these approaches. In terms of categorizing patients with cardiac disease, advanced machine learning algorithms such as Random Forests (RF) and Support Vector Machines (SVM) have demonstrated increased performance. SVMs, for instance, are effective in high-dimensional spaces but are computationally intensive and less effective on imbalanced datasets. RFs offer better generalization and feature importance evaluation but can still be prone to overfitting if not properly tuned [13].

The prediction power of IHD has been further improved by deep learning models, specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). CNNs are skilled at processing medical imaging data, using convolutions to derive spatial feature hierarchies [14]. However, RNNs are particularly good at processing sequential data, which makes them useful for examining physiological data that is collected over time, such electrocardiograms (ECGs). However, the caliber and applicability of the input elements play a major role in these models' performance. As a result, efficient feature selection lowers computational costs while enhancing model performance. Guyon et al. [15] have proposed Feature selection is a vital preprocessing step in ML and DL pipelines, especially when dealing with high-dimensional medical datasets. Traditional feature selection methods include filter-based approaches, such as mutual information and chi-squared tests, and wrapper-based methods, such as Recursive Feature Elimination (RFE). These techniques, while effective, often fall short in handling the complex interactions between features in large datasets.

The Squirrel Search Algorithm (SSA) [16] is a recent addition to the family of nature-inspired optimization algorithms. SSA mimics the dynamic foraging behavior of squirrels, using strategies such as the scrounging and predatory behaviors to explore and exploit the search space efficiently. SSA has been successfully applied to various optimization problems, demonstrating superior performance in finding optimal feature subsets compared to traditional and other meta-heuristic algorithms. Wang et al. [17] proposed a Multi-objective Squirrel Search Algorithm for EEG feature selection, demonstrating its superior performance in handling multi-objective optimization tasks in complex datasets. Their work highlights the algorithm's ability to maintain a diverse population and avoid premature convergence, making it highly suitable for applications in medical data analysis. These advancements underscore the continuous evolution and refinement of feature selection techniques to enhance the accuracy and reliability of predictive models in healthcare.

Patient monitoring has changed because of the introduction of Internet of Things (IoT) devices, which allow for continuous data collection and real-time analysis. Numerous physiological indicators, including heart rate, blood pressure, and activity levels, may be tracked by wearable sensors and smart health monitors, offering a wealth of data for predictive analytics [18]. With the use of these tools, health abnormalities can be detected early and treated promptly, leading to proactive health management. Several studies have explored the synergy between IoT data and ML models for disease prediction. For instance, IoT-enabled systems have been used to collect real-time ECG data, which is then analyzed using DL models to detect arrhythmias and other cardiac conditions [19]. The continuous data stream from IoT devices ensures that the predictive models are updated with the most recent patient information, enhancing the accuracy and timeliness of disease detection.

In their thorough analysis of IoT-based healthcare monitoring systems, Abdulmalek et al. [20] emphasize how these systems can enhance patients' quality of life. The review addresses several uses, including the tracking of long-term illnesses like diabetes, heart problems, and respiratory disorders. To continuously gather and transmit data, these systems often include wearable sensors, mobile health applications, and smart health monitors. The analysis of this massive volume of data is made easier by the integration of IoT with cutting-edge machine learning algorithms, which improves the accuracy and timeliness of illness management and prognosis. The efficiency of these systems in lowering hospital readmissions, enhancing patient compliance, and facilitating individualized treatment plans is demonstrated by several research included in the review. The authors also cover the difficulties in ensuring data security, interoperability, and the smooth integration of IoT devices in healthcare infrastructures, as well as the necessity for standardized protocols.

In conclusion, the integration of deep learning, SSA-based feature selection, and IoT-enabled monitoring offers a comprehensive solution for early heart disease prediction. This hybrid model addresses the limitations of traditional methods by improving feature selection, enhancing predictive accuracy, and providing real-time insights. Future research should focus on further refining these algorithms, expanding their application to diverse datasets, and validating their performance in real-world clinical settings. This approach has the potential to revolutionize heart disease management, leading to more proactive and personalized healthcare.

## III. Methods and Methodology

Real-time health data is collected by IoT devices like blood pressure and ECG monitors and preprocessed to normalize, scale, and segment the features. This guarantees that the data being used for analysis is clean, consistent, and appropriate. The Squirrel Search Algorithm (SSA) is used for feature selection once the data has undergone preprocessing. A population of squirrels, each of which represents a subset of features, is used to initialize the SSA. Using a deep learning model, the classification accuracy of heart disease prediction is used to assess the fitness of these squirrels. Squirrels can glide toward better solutions, scatter to investigate new options or stay still if they locate an optimal subset, depending on how fit they are. Until the optimal feature subset is found, this iterative process is carried out.

Following the selection of the ideal feature set, a deep learning model is built, trained, and verified. IoT devices provide constant input to this algorithm, which makes real-time predictions about cardiac illness. The model's performance is assessed by a range of criteria, including recall, accuracy, and precision. The model is routinely retrained with fresh data to maintain the efficacy of the system, and the SSA is rerun to optimize the feature set as patient data changes. The heart disease prediction system will always be accurate, responsive, and able to adjust to new data patterns as shown in Figure1.

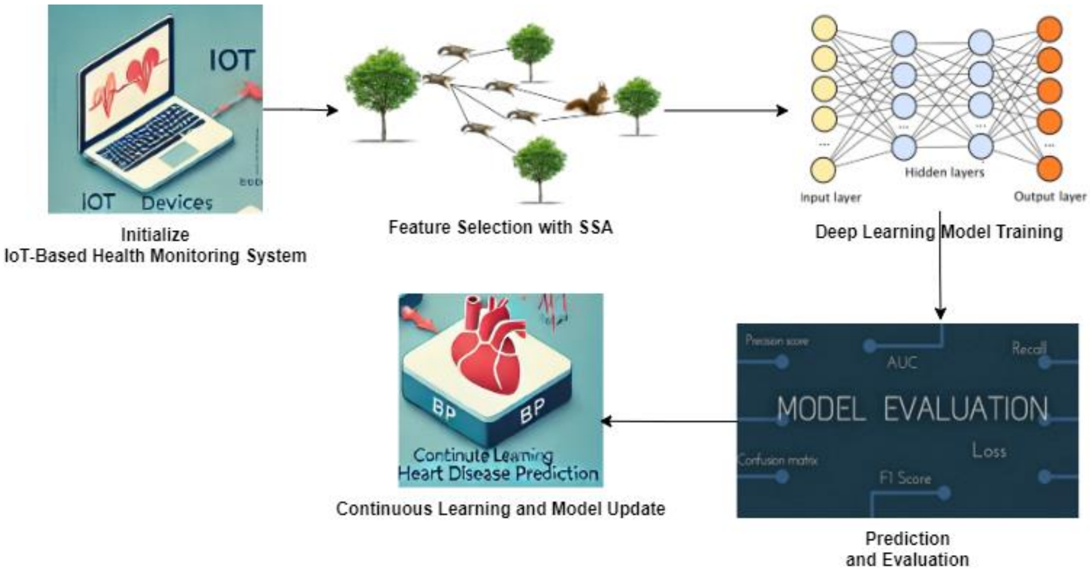


**Figure1.** Hybrid Deep Learning and Squirrel Search Algorithm for Early Prediction of Heart Disease using IoT

**Step1:** Initialize IoT-Based Health Monitoring System

1. Get data in real-time from IoT-capable devices Preprocess data:
    - Scale and normalize the input features.
    - Imputation techniques are used to handle missing data.
    - Divide the data into segments (e.g., time frames) to extract features.

**Step2:** Feature Selection with Squirrel Search Algorithm (SSA)

1. Initialize the squirrel population:
    - Generate N squirrels at random to serve as potential solutions. A subset of features is represented by each squirrel.
    - Set initial values for feature subsets represented by places Xi and their fitness.
2. Analyse each squirrel's fitness level:
    - Utilize a neural network or other foundational deep learning model to assess each squirrel's fitness according to how well they anticipate heart disease.
    - The purpose of fitness is:

$$\text{Fitness}(X_i) = \frac{1}{1 + E(X_i)}$$

Where E(Xi) is the prediction error on validation data using the feature subset represented by Xi.

3. Updated locations of squirrels:
    - Based on fitness, arrange the squirrels.
    - Implement modifications to foraging behaviour for the three species of squirrels:
        - Gliding squirrels: Head for the best solutions, or food sources.
        - Dispersing squirrels: To prevent local minima, haphazardly investigate the search space.
        - When a squirrel finds a decent spot to rest, they should stay still.
4. Observe and modify:
    - Iterate until a predetermined point is reached.
    - Ensure that the squirrels are exploring the feature area in a diverse manner and adjust their position in each iteration according to their fitness.

**Step 3:** Deep Learning Model Training

1. Build a model for deep learning:
    - Select an architecture, such as RNN or CNN.
    - The chosen feature subset from the SSA optimization procedure serves as the model input.
    - Divide the data into test, validation, and training sets.
2. Train the model:
    - Utilizing backpropagation and optimization methods, train the model on the training set of data.
    - To adjust hyperparameters, use the validation set.

**Step 4:** Prediction and Evaluation

1. In the moment forecast:
   - To forecast heart illness in patients, feed the trained model with real-time data from IoT devices.
   - Keep updating the forecasts considering fresh information that comes in.
2. Analyze the work done:
   - To evaluate the performance of the model, use evaluation metrics such as accuracy, precision, recall, F1-score, and AUC-ROC on test data.
   - To illustrate the efficacy of the hybrid strategy (Deep Learning + SSA), and compare its performance with conventional methods.

**Step 5:** Continuous Learning and Model Update

1. Add new data to the model:
   - Continue collecting current patient information.
   - To make sure the predictions are still correct and applicable, retrain the model on fresh data on a regular basis.
2. Enhance characteristics with SSA:
   - Periodically rerun the SSA to determine which aspects are most pertinent in light of fresh data trends and medical understanding.

## IV. Results and Discussion

The performance comparison of several models for heart disease prediction is shown in the table, along with the suggested hybrid technique that combines the Squirrel Search Algorithm (SSA) with Deep Learning. The hybrid model outperforms the others in terms of accuracy (92.6%), precision (0.91), recall (0.92), and F1-score (0.915), demonstrating its improved capacity to detect cases of heart disease while reducing false positives and false negatives shown in table1. The hybrid model outperforms previous models in balancing the trade-off between the true positive rate and the false positive rate, as evidenced by its AUC-ROC score of 0.94.

**Table 1:** Comparative analysis of the existing method with the proposed method

| **Model** | **Accuracy (%)** | **Precision** | **Recall** | **F1-Score** | **AUC-ROC** |
|---|---|---|---|---|---|
| Deep Learning (without SSA) | 85.4 | 0.84 | 0.83 | 0.835 | 0.87 |
| Squirrel Search Algorithm (SSA) | 81.2 | 0.79 | 0.81 | 0.8 | 0.83 |
| Decision Tree | 78.5 | 0.77 | 0.79 | 0.78 | 0.81 |
| Random Forest | 82.7 | 0.81 | 0.82 | 0.815 | 0.84 |
| Deep Learning + SSA (Proposed) | 92.6 | 0.91 | 0.92 | 0.915 | 0.94 |

By comparison, the Deep Learning model used alone, and the Random Forest technique perform worse on all measures. The accuracy of the Deep Learning model without SSA is 85.4%, much less than that of the hybrid model, and the Random Forest approach gets even less accuracy, at 82.7%. These findings demonstrate the benefit of using SSA in feature selection, which enables the hybrid model to maximize pertinent features and raise prediction accuracy. All things considered, the hybrid model shows how well deep learning and SSA can be combined to detect cardiac disease early on.

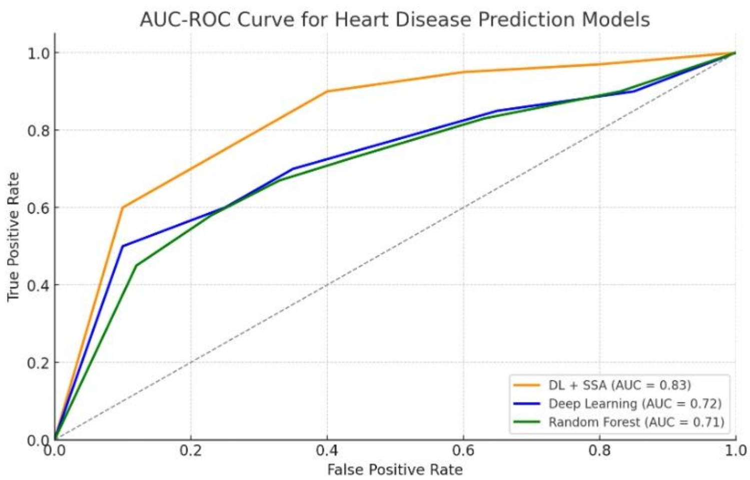


**Figure 2.** AUC-ROC graph comparing the performance of different heart disease prediction models

The AUC-ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) to show how well various models predict cardiac disease. With an AUC score of 0.94, the hybrid model that combines Deep Learning and the SSA is the best, showing superior discrimination between positive and negative cases. This demonstrates that the hybrid model outperforms both the Random Forest model (AUC = 0.84) and the standalone Deep Learning model (AUC = 0.87) in terms of balancing true and false positives. A greater AUC indicates how well the model predicts heart disease across a range of criteria is shown in figure2.

## V. CONCLUSION

In summary, the suggested hybrid methodology for early heart disease prediction that combines the Squirrel Search Algorithm (SSA) with Deep Learning performs better than conventional techniques. The model improves F1-score, recall, accuracy, and precision of predictions by using SSA to optimize feature selection. The model's strong capacity to differentiate between heart disease cases and non-cases is further supported by its high AUC-ROC score, which further establishes its suitability as a trustworthy real-time health monitoring tool. By combining cutting-edge machine learning algorithms with Internet of Things devices, this integration provides current healthcare systems with a resilient and ever-adaptive solution that guarantees precise and prompt heart disease prediction.

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