Enhancing Breast Cancer Diagnosis: A Hybrid Approach with Bidirectional LSTM and Variable Size Firefly Algorithm Optimization

Original Scientific Paper

Mandakini Priyadarshani Behera
Siksha 'O' Anusandhan (Deemed to be) University
Department of Computer Science and Engineering, Bhubaneswar, India
mandakini.beheracse@gmail.com

Archana Sarangi
Siksha 'O' Anusandhan (Deemed to be) University
Department of Electronics and Telecommunications, Bhubaneswar, India
archanasarangi@soa.ac.in

Debahuti Mishra*
Siksha 'O' Anusandhan (Deemed to be) University
Department of Computer Science and Engineering, Bhubaneswar, India
debahutimishra@soa.ac.in

*Corresponding author

Abstract *– Breast cancer stands as a significant global health challenge, ranking as the second leading cause of mortality among women. The increasing complexity of timely and accurate remote diagnosis has spurred the need for advanced technological solutions. Breast cancer prediction involves utilizing risk assessment models to identify individuals at higher risk, enabling early detection and personalized treatment strategies. This research meticulously assesses the effectiveness of various long short-term memory (LSTM) classifiers, including simple LSTM, Vanilla LSTM, Stacked LSTM, and Bidirectional LSTM, utilizing a comprehensive breast cancer dataset. Among these, the Bidirectional LSTM emerges as the preferred choice based on a thorough evaluation of accuracy, precision, recall, and F1-Score metrics. In a strategic move to further enhance precision, the Bidirectional LSTM integrates with the variable step-size firefly algorithm (VSSFF). Renowned for dynamically adjusting its step size, VSSFF offers adaptive exploration and exploitation capabilities in optimization tasks. The resulting hybrid model, HVSSFFLSTM, showcases superior performance in breast cancer prediction, suggesting potential applicability across diverse health conditions. Comparative analyses with other models highlight the exceptional accuracy rates of HVSSFFLSTM, achieving 99.78% (training) and 97.37% (testing), precision rates of 99.56% (training) and 97.22% (testing), recall rates of 100% (training) and 98.59% (testing), F1 scores of 99.82% (training) and 97.9% (testing) and specificity of 99.81% (training) and 99.15% (testing). This study not only underscores the adaptability of VSSFF as a valuable optimization tool but also emphasizes the promising prospects of the proposed hybrid model in advancing automated disease analysis. The results indicate its potential beyond breast cancer, suggesting broader applications in various medical domains.*

Keywords: *Simple LSTM, Vanilla LSTM, Stacked LSTM, Bidirectional LSTM, Firefly Optimization Algorithm, Variable Step Size Firefly Algorithm*

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1. INTRODUCTION

Breast cancer is a major health concern worldwide, underscoring the need for accurate risk assessment and early detection [1]. Machine learning (ML) and deep learning (DL) techniques are pivotal in improving detection methods [2]. ML algorithms like support vector machines (SVM), random forest, logistic regression (LR), decision trees (DT-C4.5), and k-nearest neighbours (k-NN) [3] aid in feature selection and classification. Recurrent neural networks (RNNs) [4], and long short-term memory (LSTM) [5] networks, excel in analysing mammographic images for abnormalities indicative of breast cancer [6]. Hybrid models integrating ML and

DL components offer a comprehensive approach, aiming to enhance detection accuracy. This study evaluates various LSTM classifiers—simple LSTM [5], Vanilla LSTM [7], Stacked LSTM [8], and Bidirectional LSTM [9] for breast cancer detection, with Bidirectional LSTM showing superior performance. The study introduces a hybrid model, VSSFFLSTM, combining Bidirectional LSTM with a variable step-size firefly algorithm (VSSFF) [10-12] to improve detection accuracy further. Utilizing well-established Breast Cancer Wisconsin (diagnostic) (WDBC) datasets [13] for training and validation ensures model consistency and performance.

The traditional firefly algorithm (FF) [14] static step-size hampers search effectiveness, necessitating dynamic adjustment. Initial larger step sizes are vital for identification and development, but dynamic alteration is needed with increased iterations for optimal performance. Whereas, the VSSFF improves upon FF by adapting the step size, resulting in better balance, faster convergence, and increased robustness. Integrating VSSFF with Bidirectional LSTM enhances breast cancer diagnosis by leveraging these improvements in optimization. The investigation introduces a hybrid model featuring several key contributions.

1. The hybrid breast cancer prediction model introduces a Bidirectional LSTM, improving predictive capabilities and overcoming hidden layer load challenges, marking a notable research innovation.
2. The VSSFF algorithm dynamically adjusts step size, enhancing the training efficiency of the Bidirectional LSTM by optimizing its weights, leading to an improved model with predictive accuracy and minimized mean square error (MSE) in the network output.
3. VSSFF further optimizes the Bidirectional LSTM by determining the optimal number of hidden neurons, utilizing initial random values and iterative refinement through the Adam optimizer. The integration of VSSFF with the Bidirectional LSTM forms a comprehensive strategy (HVSSFFLSTM).

This article follows a structured approach, beginning with a review of relevant literature in Section 2, followed by a comprehensive explanation of the methodologies in Section 3. Section 4 provides an analysis of the experiments conducted. Key findings are discussed in this section as well. Finally, Section 5 concludes the paper by discussing future avenues of research.

2. LITERATURE SURVEY

In Hazra et al. [15], an artificial neural network and a DT model are employed to scrutinize early-stage breast cancer characteristics, distinguishing between malignancy and benign nature. Another investigation by Naji et al. [16] analyses the BCWD dataset using five ML algorithms, providing valuable insights into their performance. A comprehensive evaluation of LSTM for breast cancer detection is conducted in a broader context by Behera et al. [17], providing insights into its capabilities. Mammographic image analysis and classification into normal, benign, and malignant classes are explored using CNN and Bidirectional LSTM architectures. According to Xia et al. [18] Innovative ensemble architectures, like the MTW CNN-BLSTM ensemble, aim to improve breast cancer prediction. In data mining methodologies, a statistical approach preprocesses data followed by a unique PSO framework for improved accuracy, sensitivity, and specificity. Multi-objective feature selection strategies incorporating ACO and PSO are developed for breast cancer diagnosis by Saturi et al. [19], enhancing detection probability by selecting relevant features. Additionally, a model named BPBRW with HKH-ABO mechanism is proposed for early-stage breast cancer diagnosis using breast magnetic imaging resonance data by Dewangan et al. [20].

The manuscript highlights a significant gap in breast cancer prediction research:

1. The absence of comprehensive comparative analyses among various ML and DL techniques.
2. Moreover, challenges in model interpretability, scalability, and generalizability remain unaddressed, indicating the need for further exploration.
3. However, there is a need for further exploration and development of ensemble techniques to enhance model accuracy and robustness.
4. Integrating innovative ensemble architectures, such as particle swarm optimization (PSO) and ant colony optimization (ACO), alongside emerging technologies like MRI data analysis, presents promising avenues for enhancing early-stage breast cancer diagnosis.
5. Therefore, future research efforts should prioritize rigorous comparative evaluations and innovative methodological advancements to bridge these critical gaps in breast cancer prediction and diagnosis.

3. METHODOLOGIES ADOPTED

In this work, simple LSTM and its variants such as; vanilla LSTM, stacked LSTM, and Bi-directional LSTM networks used. Along with this, the FF algorithm [14] is also used to optimize the positions based on fireflies' attractiveness, with intensity decreasing with the distance. Equation (1) guides the fireflies towards brighter positions, integrating attractiveness, distance, and randomness.

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_i - x_j) + \alpha(rand - \tfrac{1}{2}) \quad (1)$$

3.1. VARIABLE STEP SIZE FIREFLY ALGORITHM (VSSFF)

The VSSFF [11] algorithm is an enhanced version of the FF, designed to overcome its limitations and improve convergence rates. It emphasizes a balance between global exploration and local exploitation to maximize benefits. In FF, a constant step size hampers effective searching, necessitating dynamic adjustment for optimal exploration-convergence equilibrium. Initial larger step sizes are needed for balanced identification and development in the early stages, gradually decreasing over iterations to maintain equilibrium. The choice between large or small step sizes depends on the optimization target's definition space. In [10] to sustain equilibrium between identification and development capabilities, the initial step size (α) should be relatively larger, gradually decreasing over iterations. In [12] the choice between a large or small search step size is contingent on the optimization target's definition space; a high-dimensional space requires a larger search step size, while a lower-dimensional space benefits from a smaller search step size, optimizing the algorithm's ability to address diverse optimization challenges as stated in Equation (2). Here, the number of existing iterations $max\ generation = maxmber\ of\ iterations$. The VSSFF operational steps are stated in Algorithm 1.

$$\alpha(t) = {}^{0.4}\Big/\left(1 + \exp\left[0.015 \times \frac{(t - \max generation)}{3}\right]\right) \quad (2)$$

Algorithm 1. VSSFF operational steps [11]

Step 1: Initialize each firefly randomly.
Step 2: Evaluate the fitness function value for the initialized population.
Step-3: Assess the light intensity.
Step 4: Determine the light absorption coefficient γ.
Step 5: Evaluate the non-constant step size α using Equation (2).
Step 6: Update the position of a specific firefly towards another attractive firefly based on Equation (1).
Step 7: Calculate the latest solution and update the light intensity.
Step 8: Modify the locations of fireflies based on their rank to obtain the current optimal solution.
Step-9: End if termination conditions are met and select the optimal solution; otherwise, return to Step 2.

3.2. PROPOSED BIDIRECTIONAL LSTM NETWORK WITH VSSFF (HVSSFFLSTM) FOR CLASSIFICATION

A novel hybrid approach, HVSSFFLSTM, integrates Bidirectional LSTM with VSSFF to enhance breast cancer classification accuracy. VSSFF collaborates with Bidirectional LSTM to optimize architecture and hyperparameters for this purpose. Bidirectional LSTM captures temporal dependencies, while VSSFF explores hyperparameter space for crucial configurations. The potential of this hybrid technique can be further realized through meticulous parameter tuning and rigorous model validation of Bidirectional LSTM. Prudent adjustment and robust validation promise enhanced performance and reliability of HVSSFFLSTM, contributing significantly to accurate breast cancer classification. In this framework, VSSFF optimizes Bidirectional LSTM parameters, particularly focusing on weight optimization. The VSSFF algorithm systematically assesses the ideal number of hidden neurons within each hidden layer. Initial random values are assigned to the primary weights of the network, and an Adam optimizer with maximum epoch=100, batch size=512, initial learning rate=0.001, grounded in gradient descent principles, is utilized to iteratively refine these network weights. Subsequently, the model undergoes comprehensive testing to gauge its performance following the adjustments made by the VSSFF algorithm. This approach not only underscores the pivotal role of weight optimization in fine-tuning the predictive capabilities of the Bidirectional LSTM but also highlights the significance of determining the optimal number of hidden neurons to elevate overall model efficacy. The integration of the VSSFF algorithm with the Bidirectional LSTM reflects a holistic strategy aimed at achieving optimal predictive accuracy in the context of breast cancer data classification. The workflow of the manuscript is presented in Fig.1. A concise mathematical representation of the hybrid model VSSFF is presented below as Equation (3), where let θ denote the set of parameters to be optimized, J(θ) represents the objective function related to breast cancer classification, and the VSSFF optimization process is denoted as by Equation (3).

$$\theta\ new = VSSFF\ (\theta\ old, J\ (\theta\ old)) \quad (3)$$

Let, w represents the weights of the hidden layers in Bidirectional LSTM. The model is denoted as Bidirectional LSTM (w). The optimized parameters θ* from the VSSFF algorithm are used to fine-tune the weights of the Bidirectional LSTM model. The VSSFFLSTM model is represented as (θ*,w*), where w* are the adjusted weights. The optimization process involves iteratively updating the parameters θ using the VSSFF algorithm as stated in Algorithm 2.

Algorithm 2. The proposed HVSSFFLSTM algorithm

Step 1: Let D represent the breast cancer dataset, with corresponding class labels (benign: $y = 0$, malignant: $y = 1$) and split D into training (D_{Train}) and testing (D_{Test}) sets.
Step 2: Initialize a population P of fireflies with random hyperparameters.
Step 3: Define the Bidirectional LSTM model architecture, specifying parameters such as the number of LSTM layers, units, and dropout rates.
Step 4: Train the Bidirectional LSTM model on D_{Train} to obtain initial weights $w_{initial}$ Evaluate the model's performance on the D_{Train} and D_{Test} using binary cross-entropy.
Step 5: Develop the VSSFF approach to optimize the hyperparameters of the Bidirectional LSTM model.

Step 6: Define the hyperparameter space Θ, including the number of LSTM layers, units, dropout rates, etc.

Step 7: Create a firefly population F, where each firefly f_i is represented by a set of hyperparameters $\theta_i \in \Theta$.

Step 8: Define the fitness function $J(\theta_i, D_{Train})$ based on the training dataset.

Step 9: Implement the variable step size method, adjusting the step size based on firefly brightness.

Step 10: Select the hyperparameters θ^* from the firefly population F based on the highest brightness, optimizing the Bidirectional LSTM model.

Step 11: Train the Bidirectional LSTM model using the optimized hyperparameters θ^*, resulting in final weights w_{final}. Evaluate the final model's performance on the D_{Test}.

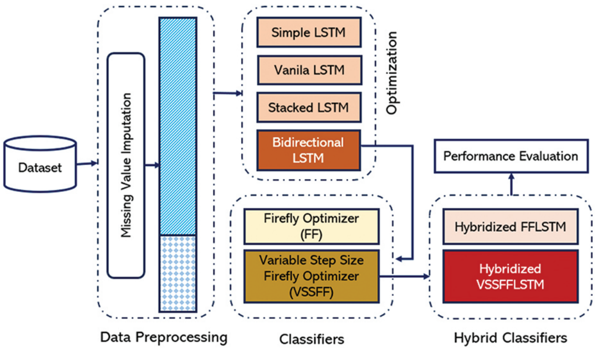

Fig. 1. Schematic layout of the proposed strategy for breast cancer prediction

3.3. DATASET AND MISSING VALUE IMPUTATION

The manuscript utilizes the WDBC dataset from the UCI ML repository [13], comprising 569 records with a distribution of 62.7% benign and 37.3% malignant breast cancer cases. Each record includes an ID number, diagnostic label (B for benign, M for malignant), and 30 real-valued input features representing significant cell nuclei characteristics such as radius, texture, perimeter, etc. Missing values in the dataset are imputed with 0 or 1 based on their respective values <50 or >=50. 80% of the dataset is used for training the model, while the remaining 20% is reserved for evaluating the model's performance.

4. EXPERIMENTAL ANALYSIS

In this section, we conduct comprehensive experimental analyses to assess the performance of our proposed model. We compare our results with various models using diverse performance metrics to gain insights into the effectiveness and superiority of our approach. The LSTM classifier is trained with 100 epochs, a batch size 512, and the Adam optimizer for optimization. The experiments were executed on a system equipped with a 1.80 GHz Intel(R) Core (TM) i5-8265U processor and 8.00 GB RAM, running on the Windows 10 operating system. All ML approaches discussed in this study were implemented using the Scikit-learn library and the Python programming language.

4.1. PARAMETERS USED

The training parameters used in this manuscript are outlined in Table 1, and Table 2 provides the parameter settings for the discussed hybrid models.

Table 1. Training Parameters

Optimizer	Maximum Epoch	Batch Size	Initial Learning Rate
Adam	100	512	0.001

Table 2. Parameter setting for hybrid models

Hybrid Models	Population Size	Iteration	Upper Bound	Lower Bound
HFFLSTM	50	200	5	-5
HVSSFFLSTM	50	200	5	-5

4.2. RESULTS ANALYSIS

This research follows a structured experimental approach consisting of two phases. Initially, four variants of LSTM networks are thoroughly explored, with Bi-directional LSTM showing superior performance across various evaluation metrics. The Bi-directional LSTM likely achieved the highest values for all metrics due to its ability to capture bidirectional contextual information, generate comprehensive feature representations, reduce information loss, effectively handle temporal dependencies, and maintain robustness to input variability, which collectively contribute to its superior performance compared to other LSTM variants. Encouraged by these results, the research progresses to the second phase, focusing on optimizing Bidirectional LSTM with FF and VSSFF algorithms. This transition marks a strategic progression, aiming to uncover and capitalize on the most effective configurations for robust performance in breast cancer prediction.

The initial experimentation phase, detailed in Table 3, meticulously analyses various LSTM model variants across training and testing datasets. Results highlight the Bidirectional LSTM's distinct superiority, demonstrating exceptional performance in both phases. In training, it achieves 96.70% accuracy, 97.90% precision, 96.89% recall, 97.40% F1-Score, and 97.79% specificity. In testing, the Bidirectional LSTM outperforms alternative variants with 96.49% accuracy, 97.18% precision, 97.18% recall, 97.18% F1-Score, and 97.18% specificity.

Table 3. Performance of different variants of LSTM

Execution Stages	Performance Metrics (in %)	Simple LSTM	Vanilla LSTM	Stacked LSTM	Bi-directional LSTM
Training	Accuracy	95.16	96.04	96.48	96.70
	Precision	94.59	98.22	97.56	97.90
	Recall	97.90	95.51	96.89	96.89
	F1-Score	96.21	96.58	97.23	97.40
	Specificity	94.78	94.97	95.86	97.79
Testing	Accuracy	95.61	94.73	92.10	96.49
	Precision	96.96	95.52	95.31	97.18
	Recall	95.52	95.52	91.04	97.18
	F1-Score	96.24	95.52	93.12	97.18
	Specificity	95.88	95.93	95.11	97.18

Table 4. Performance of HFFLSTM and HVSSFFLSTM models

Execution Stages	Performance Metrics (in %)	HFFLSTM	HVSSFFLSTM
Training	Accuracy	99.34	99.78
	Precision	98.96	99.56
	Recall	1.00	1.00
	F1-Score	99.47	99.82
	Specificity	98.85	99.81
Testing	Accuracy	96.49	97.37
	Precision	98.55	97.22
	Recall	95.77	98.59
	F1-Score	97.14	97.9
	Specificity	97.12	99.15

The empirical findings strongly support the Bidirectional LSTM as the most promising variant, leading to its strategic selection for optimization. The VSSFF algorithm is then employed to enhance its predictive capabilities further. The optimization aims to fine-tune and improve key performance metrics like accuracy, precision, recall, and F1-Score in breast cancer prediction, contributing to more reliable outcomes in medical diagnostics. The exploration extends to hybridized forms of Bidirectional LSTM, including HFFLSTM and HVSSFFLSTM. In HFFLSTM, the FF algorithm integrates seamlessly with Bi-directional LSTM, optimizing hyperparameters to enhance pattern recognition capabilities by fine-tuning parameters such as layer numbers, units, and dropout rates. Conversely, HVSSFFLSTM combines the VSSFF algorithm with Bi-directional LSTM, introducing dynamic step-size adjustment for efficient hyperparameter exploration. The FF algorithm optimizes hyperparameters, while VSSFF introduces dynamic step-size adjustment, facilitating more efficient exploration of the hyperparameter space. The experimental evaluations include accuracy plot analyses and comprehensive performance metrics. These assessments highlight the superior predictive capabilities of HVSSFFLSTM, showcasing its potential to advance breast cancer prediction models compared to HFFLSTM and other existing approaches. Subsequent sections provide a detailed exploration of this experimentation phase, offering insights into the optimization process intricacies and innovative strides toward enhancing breast cancer prediction models.

Within Table 4, we meticulously conduct a comparative analysis, delving into the nuanced distinctions between HFFLSTM and HVSSFFLSTM. The outcomes of this detailed examination underscore the consistent superiority of HVSSFFLSTM over HFFLSTM during the training phase, boasting remarkable metrics such as accuracy (99.78%), precision (99.56%), recall (100%), F1-Sscore (99.82%) and specificity (99.81%). In the testing phase, HVSSFFLSTM continues to excel, demonstrating impressive performance in accuracy (97.37%), recall (98.59%), F1-Sscore (97.9%), and specificity (99.15%). Albeit with a marginally lower precision (97.22%) when juxtaposed with the HFFLSTM model, which registers at (98.55%). This minor discrepancy is deemed manageable, affirming the overall robustness of HVSSFFLSTM.

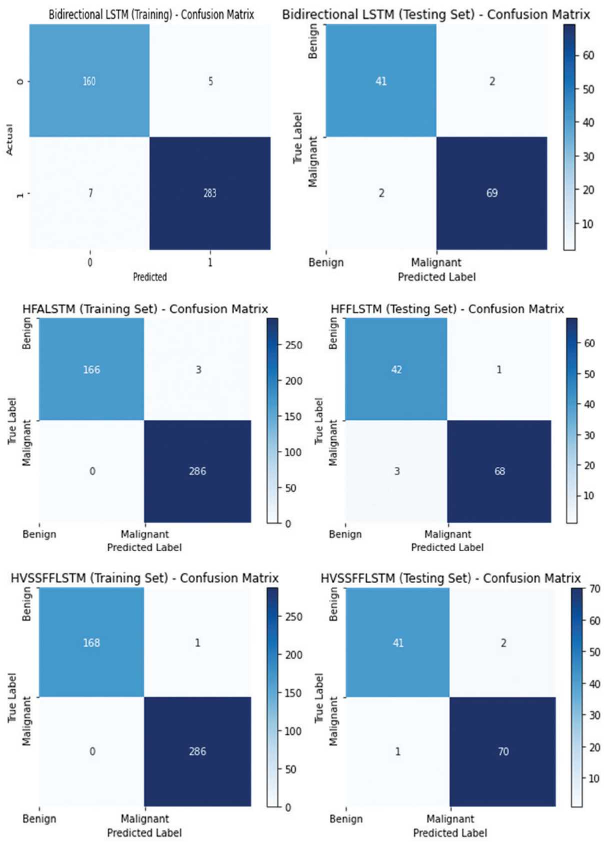

Fig. 2. Confusion matrix for training and testing with Bidirectional LSTM, HFFLSTM, and HVSSFFLSTM

Fig. 2. illustrates confusion matrices for Bidirectional LSTM, HFFLSTM, and VSSFFLSTM models in breast cancer prediction across training and testing phases. VSSFFLSTM stands out with significantly elevated accuracy compared to Bidirectional LSTM and HFFLSTM, indicating its superior performance. Subsequent meticulous assessment of classification performance, considering

metrics like accuracy, precision, recall, and F1-Score, unveils the nuanced advantages of HVSSFFLSTM over its counterparts. This analysis showcases HVSSFFLSTM's ability to deliver accurate and reliable predictions in breast cancer prediction. Visualization of confusion matrices and detailed performance analysis not only quantitatively evaluates models but also highlights HVSSFFLSTM's strengths and capabilities. This empirical evidence substantiates the efficacy and potential superiority of the proposed model, emphasizing its significance in advancing breast cancer prediction methodologies.

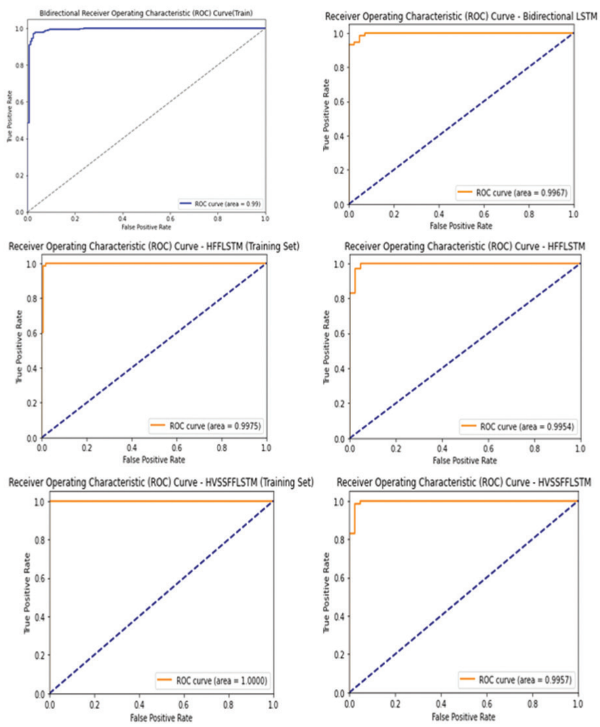

Fig. 3. ROC curve results for training and testing with Bidirectional LSTM, HFFLSTM, and HVSSFFLSTM

Fig. 3. illustrates the graphical ROC analysis for Bidirectional LSTM, HFFLSTM, and VSSFFLSTM in breast cancer prediction, showcasing the true positive rate (TPR) versus false positive rate (FPR) for both training and testing datasets. Specifically, the ROC values for Bidirectional LSTM are 99% for training and 99.67% for testing, while HFFLSTM achieves 99.75% for training and 99.54% for testing. Notably, the ROC curve values for the proposed HVSSFFLSTM algorithm stand at 100% for training and 99.57% for testing. These results highlight the exceptional discriminative performance of the HVSSFFLSTM model in effectively distinguishing between TP and FP during breast cancer prediction.

Fig. 4. presents graphical representations showing the dynamic fluctuations in accuracy across epochs during both training and testing phases for Bidirectional LSTM, HFFLSTM, and HVSSFFLSTM models in breast cancer prediction. These visuals offer insights into the evolution of accuracy for each model throughout the training and testing processes, aiding in understanding the learning trajectories and performance trends. The fluctuations in accuracy over epochs enable observation of how each model adapts and refines its predictive capabilities with iterative learning, which is crucial for evaluating stability, convergence, and overall learning efficiency. Fig. 4. serves as a visual narrative, providing a comprehensive overview of the learning dynamics exhibited by the models during breast cancer prediction, enhancing understanding of temporal aspects of model performance, and identifying key epochs influencing predictive power.

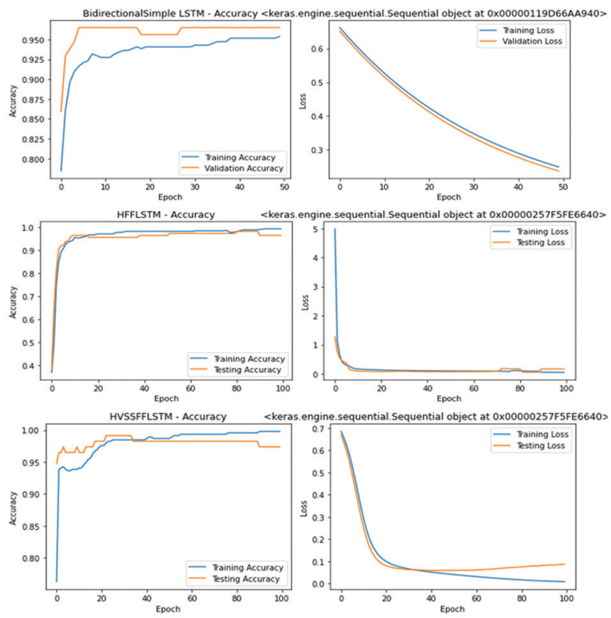

Fig. 4. Comparison of accuracy achieved for training and testing with Bidirectional LSTM, HFFLSTM, and HVSSFFLSTM

The efficacy of the VSSFF algorithm lies in its adaptive step size, dynamically balancing exploration and exploitation. This addresses the limitations of a fixed step size, preventing suboptimal results. The algorithm enables more effective navigation through intricate optimization landscapes and contributes to faster convergence toward optimal solutions by refining its exploration strategy through iterations. Its robustness across various optimization problems provides flexibility to adapt exploration strategies based on landscape characteristics. These features render the VSSFF algorithm more effective than the FF algorithm. Consequently, this research proposes a more robust model HVSSFFLSTM for breast cancer data classification, leveraging the enhanced capabilities of the VSSFF algorithm.

4.3 STATISTICAL VALIDATION AND EXECUTION TIME COMPARISON

Table 5 displays the McNemar test [21] results comparing HFFLSTM vs. Bidirectional LSTM and HVSSFFLSTM vs. HFFLSTM models in training and testing phases, revealing significant performance differences. HVSSFFLSTM demonstrates the shortest training and testing times, outperforming other models.

Table 5. McNemar's test results

Execution Stages	Tests and p-values	HFFLSTM vs. Bidirectional LSTM	HVSSFFLSTM vs. HFFLSTM
Training	McNemar Test Statistic	5.21	7.78
	p-value	0.022	0.005
Testing	McNemar Test Statistic	5.68	4.89
	p-value	0.0171	0.026

Fig. 5 compares execution times (in milliseconds) for Bidirectional LSTM, HFFLSTM, and HVSSFFLSTM models. HVSSFFLSTM demonstrates the shortest training time at 2.87 ms, followed by HFFLSTM at 3.46 ms and Bidirectional LSTM at 4 ms. In testing, HVSSFFLSTM also shows the fastest execution time at 2.11 ms, outperforming HFFLSTM (3.44 ms) and Bidirectional LSTM (3.55 ms). These results underscore HVSSFFLSTM's superior efficiency in both the training and testing phases.

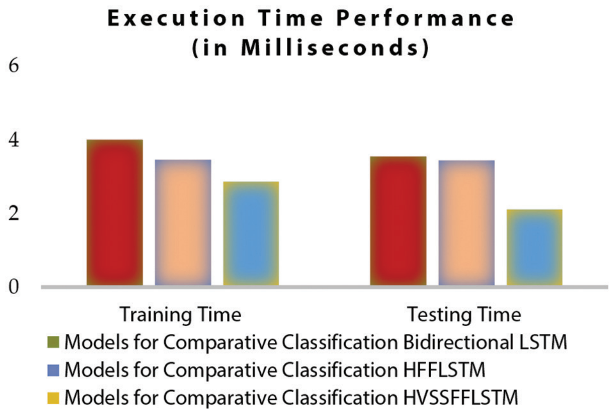

Fig. 5. The recorded performance in terms of execution time

4.4. PRINCIPAL INSIGHTS AND DISCUSSIONS

This section provides a detailed analysis of LSTM networks for breast cancer prediction in two phases. Four LSTM variants are initially explored, with Bidirectional LSTM identified as the most promising. Bidirectional LSTM is then optimized using FF and VSSFF algorithms to enhance predictive capabilities, leading to hybrid forms like HFFLSTM and HVSSFFLSTM. Experimental evaluations highlight HVSSFFLSTM's superior predictive capabilities, confirmed by accuracy plots, ROC analyses, and comprehensive metrics. Comparative analysis consistently favors HVSSFFLSTM, with statistical validation confirming its significance. HVSSFFLSTM also demonstrates computational efficiency, positioning it as a promising candidate for resource optimization. These findings contribute to a deeper understanding of model efficacy and computational efficiency in breast cancer prediction.

The proposed classification models consistently exhibit robust performance across training and testing phases, with HVSSFFLSTM showing superior performance. During training, HVSSFFLSTM achieves exceptional results with 99.78% accuracy, 99.56% precision, 100% recall, 99.82% F1 Score, and 99.81% specificity. Testing also demonstrates strong performance with 99.37% accuracy, 97.22% precision, 98.59% F1 Score, and 99.15% specificity. Statistical validation and execution time performance solidify HVSSFFLSTM as a noteworthy advancement in breast cancer detection research, showcasing its precision and reliability in classification.

5. CONCLUSION AND FUTURE SCOPE

This study thoroughly examines four LSTM algorithms and two hybrid models for breast cancer classification. Results consistently show the superiority of the proposed hybrid model. HVSSFFLSTM, HFFLSTM, and Bidirectional LSTM are ranked as the top three models. The study suggests avenues for future exploration, including additional hybrid models and diverse datasets. The proposed predictive methods demonstrate versatility, with potential applications in various medical conditions beyond breast cancer. This research sets the stage for continued innovation in medical predictive modelling.

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