An Improved LNN–ACO Framework with Optimal Feature Selection for Breast Tumor Detection

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ABSTRACT

Conventional image processing approaches, such as segmentation and feature extraction, may not perform effectively across different histopathological images due to highly variable structures. In addition, histopathological images are high-dimensional with gigapixel slides. However, the dynamic nature of cellular structures, temporal changes, and variations in nuclear size and shape present substantial challenges in terms of complex structure and staining variability. In addition, training deep CNN models from scratch may lead to overfitting. To address these issues, this study combines Liquid Neural Networks (LNN) with Ant Colony Optimization (ACO) (LNN-ACO) for breast tumor detection, reducing redundant features and fine-tuning model parameters, leading to a more discriminative feature space. Experimentation with the BreakHis dataset showed that the proposed LNN-ACO model achieved 93.75% accuracy, outperforming other techniques.

Keywords-breast cancer classification; liquid neural networks; ant colony optimization; machine learning; medical image analysis; AI in healthcare

I. INTRODUCTION

Deep learning is widely adopted to diagnose medical images due to its high efficiency in classifying and detecting diseases. This state-of-the-art technology is an important tool in medical imaging and diagnostics [1]. However, AI-based diagnostic systems still face several shortcomings in terms of adaptability to real-world data, sensitivity to imaging noise, and high computational demands. Traditional deep-learning models suffer from major drawbacks, such as overfitting, relying on specific annotated datasets, and failing to generalize from one imaging condition to another. All these disadvantages highlight the need to build very efficient, flexible, and computationally optimized AI-driven medical imaging diagnostic models for reliable and automated breast cancer classification [2].

In [3], a Genetic Algorithm was hybridized with Ant Colony Optimization (GACO) for feature selection, achieving better efficacy and accurate breast tumor detection. In [4, 5], ACO was used for the detection of breast cancer. However, deep learning techniques are more robust than classical classifiers in feature extraction and complex pattern recognition [5]. In [6], Liquid Neural Networks (LNNs) were introduced as an alternative to standard deep learning models. LNNs function with internal state variables of their neurons that can change dynamically, granting a high degree of adaptability to handling noise and high-dimensional data arising from medical imaging. The study in [7] focused on Computer-Aided Diagnosis (CAD) to enhance feature extraction and classification. Hybrid ACO (HACO) helps to strengthen segmentation accuracy across several domains, such as healthcare, robotics, and remote sensing [8, 9]. In [10], an LNN framework was capable of handling sequential tasks in medical imaging, showing that such models outperform traditional CNNs and LSTMs in classification tasks, making them suitable for dynamic medical applications. In [11-14], deep and generative adversarial learning techniques were proposed for the early diagnosis of breast cancer.

Histopathological images are high-dimensional due to gigapixel slides. However, the dynamic nature of cellular structures, temporal changes, and variations in nuclear size and shape present substantial challenges in terms of complex structure and staining variability. Training deep CNN models from scratch can lead to overfitting. To address these issues, this study combines Liquid Neural Networks (LNN) with Ant Colony Optimization (ACO) (LNN-ACO) for the detection of breast tumors. The proposed LNN-ACO model reduces redundant features and fine-tunes model parameters, leading to

a more discriminative feature space. Moreover, LNN utilizes differential equations that can capture dynamic changes over time to identify anomalies in histopathology images. In addition, the LNN can dynamically change its neuron states, effectively handling noisy and high-dimensional images. With the integration of ACO, the proposed model attains optimal feature selection and hyperparameter settings, reducing computational cost and improving model efficacy. The major contributions of this study can be summarized as follows:

- Adapts ACO for feature selection to explore the most relevant features, enhancing classification accuracy and reducing irrelevant features.
- Proposes the LNN-ACO model to capture temporal and spatial dependencies in histopathological images for breast tumor detection.
- Adapts ACO for hyperparameter tuning to enhance model efficacy.
- Experimentation with the BreakHis dataset showed that the proposed LNN-ACO model achieved 93.75% accuracy, outperforming other techniques.

II. METHODOLOGY

The proposed AI-based breast cancer classification system integrates LNNs and ACO to increase diagnostic accuracy, computational efficiency, and robustness against imaging variations. The proposed system can process histopathological images, extract relevant tumor features, optimize feature selection, and classify tumors as benign or malignant. Unlike standard deep learning models, which assume static feature representations, this method utilizes dynamic activation-based learning along with bio-inspired optimization techniques, maximizing both adaptability and efficiency.

A. Data Preprocessing and Feature Extraction

Histopathological images show considerable differences in color intensity, contrast, and texture due to variations in staining methods, microscope settings, and imaging conditions. Thus, a strong preprocessing pipeline is needed to normalize, enhance, and extract meaningful tumor features for classification. Histopathological images in the BreakHis dataset are displayed at a total of four magnifications: 40×, 100×, 200×, and 400×. All images are standardized through preprocessing and feature extraction before classification. The preprocessing pipeline steps are as follows:

- Color Normalization: Reinhard color transformation was applied to normalize the color intensities across all samples.
- Contrast Enhancement: Tumor areas were highlighted using Adaptive Histogram Equalization (AHE).
- Augmentation: Rotation, flipping, brightness changes, and scaling were used to enhance model generalization.
- Pixel Intensity Normalization: Pixel values were normalized in [0,1] to stabilize the deep learning model.

B. Liquid Neural Networks-Ant Colony Optimization (LLN-ACO) Model for Classification

LNNs, unlike static deep learning models such as CNNs and fully connected neural networks, continuously update the condition of their neurons as a function of the complexity of the input data. This makes them especially useful in certain medical imaging applications, where variability in staining intensity, image resolution, and noise level can greatly affect classification performance. An LNN model can effectively extract feature maps by optimizing hyperparameters for accurate tumor detection. Conventional neural network models use static activation functions. LNNs are modeled by considering Ordinary Differential Equations (ODEs) or dynamic liquid neurons. In addition, the activation function of each liquid neuron changes over time depending on the input and internal states. This distinguishes it from other conventional methods, as it encourages refinement in continuously evolving representations, resulting in superior classification robustness, exceeding normal CNNs in medical imaging applications. During training, the LNN classifier processes the feature vectors to ensure that only the most relevant features to the tumor are used for classification. A 70-15-15 split of the BreakHis dataset was used to train, validate, and test the model, respectively, ensuring a fair evaluation, preventing overfitting, and allowing generalization across various magnification levels.

C. Liquid Neural Networks Module

LNNs are built using parametric first-order dynamical models, where the behavior of the model is regulated to capture temporal and spatial dependencies in histopathological images [15]. Relying on ODE solvers provides continuous adaptation to spatial variability and complex histopathology patterns. In addition, ODE solvers model the dynamic changes of hidden states [16]. For histopathology images, the time constants in the LNNs represent the continuity and stability of patch-level features and the speed with which the trained model adjusts to local variability. This leads to capturing global contextual information with fine-grained features that help to accurately classify tumors. In LNNs, closed-form solutions reduce the computational cost of hidden states with ODE-based dynamic neurons. The closed-form updates improve the efficiency of hidden state computation. Due to exponential decay, patch-level features in histopathology images can lead the LNN to convergence quickly in a biased state [17]. To address this issue, non-linearity was introduced through a sigmoid function instead of an exponential term.

In histopathology analysis, LNNs suffer from training instability and parametric divergence, and are sensitive to hyperparameters and optimization challenges due to the dynamic nature of tissue patterns. Extracting higher-order tissue representations from histopathology images may not be effective due to the non-convexity of the LNN architecture, reducing the overall model performance. The proposed LNN is optimized through ACO, achieving more stable and robust feature learning. This approach integrates LNNs to extract temporal domain features, with high-order tissue patterns extracted from the ACO algorithm, leading to improved optimization performance.

D. Ant Colony Optimization for Feature Selection and Hyperparameter Tuning

Feature selection is essential in medical imaging classification, as superfluous and irrelevant features introduce noise and affect model performance. ACO starts with the initialization of the artificial ant colony, which provides the ants with the possibility of exploring various subsets of extracted features. These ants evaluate the feature subsets according to classification accuracy, with pheromone enhancement with respect to the selection of features in subsequent iterations. Gradually, after several iterations, an optimal feature subset is selected, minimizing dimensionality and maximizing diagnostic information density.

ACO is applied not only for feature selection but also for hyperparameter tuning to optimize parameters such as learning rate, dropout rate, and batch size, ensuring convergence stability during training. Dynamic adjustment of model hyperparameters leads to a gain in accuracy with minimal computational overhead, which fits the requirements for real-time clinical deployment.

Figure 1 shows the proposed LNN-ACO method. The LNN captures temporal dependencies and dynamic patterns in the histopathology images. The LNN architecture contains an input layer, multiple hidden layers, and a readout layer. The input layer is acquired from ACO by selecting the optimal feature space, multiple hidden layers with recurrent liquid-state dynamics, where each neuron acts as a dynamic reservoir that captures non-linear feature interactions, and the readout layer that maps high-dimensional states to the output layer for classification. Thus, the LNN can effectively capture non-linear patterns from histopathology images and is more robust to handle variability across tissue structures.

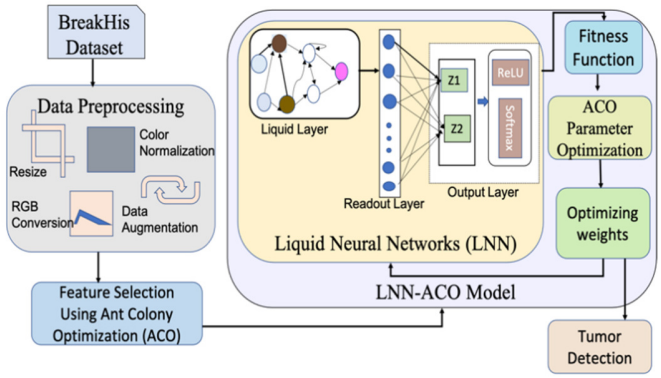

Fig. 1. LNN-ACO framework for breast tumor detection.

In the ACO feature selection component, each ant selects a subset of features through stochastic exploration based on the pheromone values that represent the weight assigned to each feature. The feature subsets that offer higher accuracy have pheromone updates, helping to ignore redundant and irrelevant features. The selected features are passed to the LNN model. ACO is also adapted to optimize the LNN hyperparameters, such as regularization coefficients, learning rate, and number of neurons in the hidden layers.

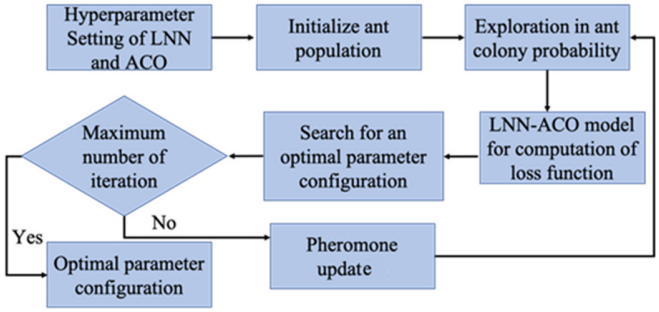

Fig. 2. ACO parameter optimization phase.

In ACO parameter optimization, each ant explores different parameter sets, guided by pheromone updates. After several iterations, the proposed model converges toward an optimal parameter configuration that yields a higher classification accuracy for breast tumor detection. This process provides robustness in that the LNN considers only the optimal subset of features and is tuned with optimal hyperparameters to improve efficacy. The algorithmic steps of the proposed LNN-ACO are as follows:

1. Initialize the ant population, pheromone levels, set of candidate features, and sets of different parameter combinations.
2. Feature Selection Using ACO: Each ant stochastically chooses a subset of features based on heuristic information, which represents the most discriminative ones before the update of pheromone levels.
3. Model Performance: The selected features are fed to train the LNN model and determine the classification accuracy of breast tumors.
4. ACO Parameter Optimization: Each ant explores LNN hyperparameters such as the regularization coefficients, learning rate, and the number of neurons in hidden layers.
5. Pheromone Update: Higher pheromone updates are rewarded when the feature subsets and hyperparameter settings achieve higher accuracy.
6. LNN-ACO Model Convergence: Steps 2-5 are iteratively repeated until there is no significant improvement in terms of accuracy over iterations.

III. RESULTS AND DISCUSSION

The performance of the proposed AI-based breast cancer classification system was evaluated qualitatively and quantitatively. Experimentation was performed on the BreakHis dataset [18], which contains histopathology images acquired from 82 patients. The LNN-ACO model was evaluated in terms of accuracy, precision, and recall.

Figures 3 and 4 show the loss and accuracy for training and validation, respectively, over several epochs. During training, the loss drops and accuracy increases, which is a good sign of learning and convergence. The ups and downs in validation accuracy indicate a complex dataset that can help in generalization across unseen samples.

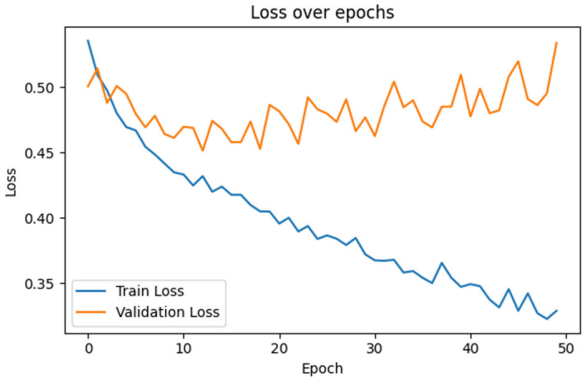

Fig. 3. Training and validation loss trends.

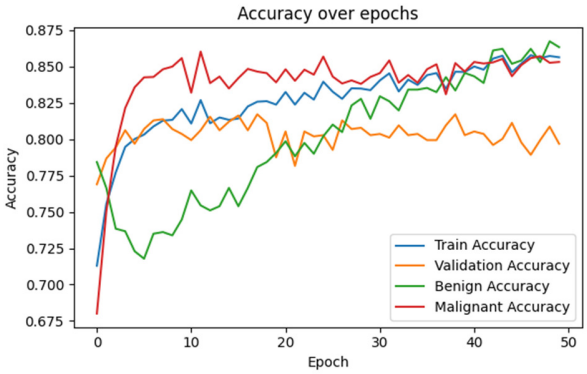

Fig. 4. Training and validation accuracy trend.

A. *Quantitative Performance Analysis*

The experimental results of the LNN-ACO model showed 93.75% overall classification accuracy, with low false positives and false negatives. However, a slight variation toward false negatives was observed, likely due to the overlap of histopathological features of benign and malignant tissues.

Figure 5 shows the classification report of the proposed LNN-ACO model for benign and malignant histopathological images. The model achieved a high true positive rate in benign tumors, which illustrates that it is sensitive to histopathological tissue patterns. However, it achieved less precision for malignant tumors, as some malignant tumors were detected as benign ones. This indicates that morphological similarities can be observed between benign and malignant histopathological tissue patterns. The model must have high sensitivity (recall) and specificity. High recall means that few malignant cases can be misclassified, and high specificity controls false positives to avoid unnecessary medical procedures. The F1 score, which balances precision and recall, is consistently high and thus validates the model's reliability.

Table I illustrates a performance comparison of the proposed LNN-ACO with other existing models on the BreakHis dataset. As can be observed, the proposed LNN-ACO model achieved higher accuracy.

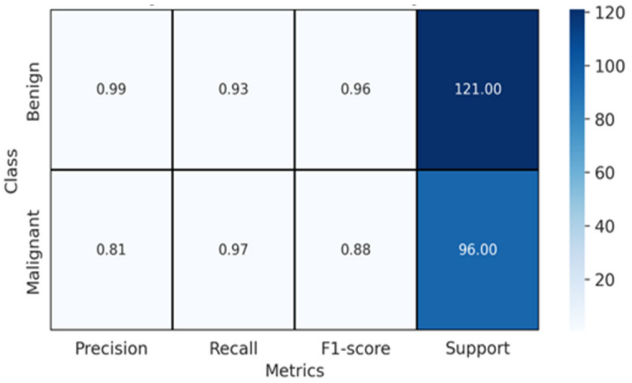

Fig. 5. Classification report.

TABLE I. PERFORMANCE COMPARISON OF THE PROPOSED OVER OTHER MODELS USING THE BREAKHIS DATASET

Method	Accuracy
Proposed LNN-ACO	93.75%
Without ACO	88.32%
SVM [19]	~88%
Ensemble bagged tree classifier [20]	89.7%

B. *Qualitative Analysis of Model Predictions*

Figures 6 and 7 depict probability scores of the proposed LNN-ACO model for benign and malignant tumor samples, respectively, reflecting the model's confidence level. For a benign tumor sample, the proposed LNN-ACO model attained a high probability (>90%), indicating it could effectively differentiate benign tissues with a high confidence value. Figure 6 shows the confidence score of the proposed LNN-ACO model on a malignant sample.

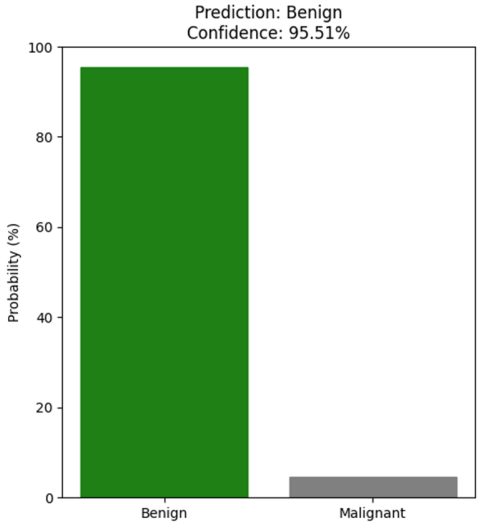

Fig. 6. Benign Tumor Prediction Output

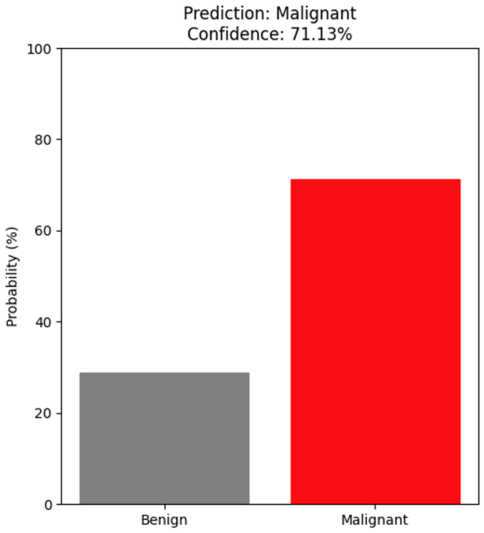

Fig. 7. Malignant tumor prediction output.

C. Evaluation, Limitations, and Future Enhancements

The proposed LNN-ACO model achieved an average accuracy of 93.75%, outperforming existing models. The first reason for its performance is that hyperparameter selection affects the convergence rate and improves its generalization. In addition, the LNN model was optimized through the ACO algorithm to achieve more stable and robust feature learning. The second reason is that the LNN extracts temporal domain features with high-order tissue patterns, leading to improved optimization performance. Due to the iterative nature of the proposed LNN-ACO, different combinations of contextual tissue features are explored, converging toward an optimal subset of contextual tissue-based features that enhances model performance. For histopathology images, the fitness is evaluated using the LNN model. The fitness value of each candidate solution is evaluated using F1-score, balancing recall and precision, and is highly suitable for histopathology image analysis across 5-fold cross-validation.

One of the major limitations of the proposed LNN-ACO is that it relies on ground-truth data. In addition, the model lacks explainability features to help radiologists interpret and improve the early diagnosis of breast cancer. Moreover, patch-level segmentation plays a significant role in delineating the tissue region of interest and other major components that contribute to accurate tumor classification.

IV. CONCLUSION

Traditional machine learning and deep learning approaches may not effectively detect tumors across different histopathological images due to their highly variable structures. Histopathological features may differ between patients and radiological environments. In addition, the images used in the training may not offer flexibility in capturing different histopathology patterns. Convolutions may not effectively capture global spatial features, which are essential for tumor segmentation. To address this issue, this study developed LNN-ACO for breast tumor detection, providing robust dynamic adaptability to time-varying and condition-dependent patterns, improving the generalization of semantic features against imaging variability. Experimentation with the BreakHis dataset showed that the proposed LNN-ACO model achieved 93% accuracy, outperforming other existing techniques.

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