SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I5P102

Volume 13 Issue 5, 13-20, May 2026
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Original Article

Attention-Enhanced LSTM and Transformer-Based Multi-Scale Feature Extraction Optimized with LOA for Robust Cervical Cancer Detection

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Received: 05 February 2026 Revised: 04 March 2026 Accepted: 03 April 2026 Published: 27 May 2026

Abstract - *Cervical cancer continues to be a major disease in the world, especially in low-resource countries, where early and accurate diagnosis is often difficult. It has offered promising ways for automated medical image analysis in recent years; yet, issues related to extracting features for robust cervical cancer detection with LOA optimization need to be addressed. Therefore, in this study, cervical cell images were preprocessed using attention-enhanced LSTM and extracted features. The AE-LSTM component captures sequential and contextual dependency in derived features, and preprocessing to transformer-based multi-scale feature extraction on a transformer encoder with LOA optimization. Experimental evaluation on benchmark cervical cancer datasets shows a better overall performance in terms of training accuracy curve, training loss curve, confusion matrix, ROC curve, precision-recall curve, model comparison bar graph, LOA convergence Plot, and Feature Visualization (t-SNE). It developed a transformer encoder to produce either normal or abnormal diagnosis output. Future work will include domain adaptation for low-resource environments, combination with multi-modal clinical data, and the design of lightweight models suitable for the deployment of real-time cervical cancer screening systems.*

Keywords - *Robust Cervical Cancer Detection, Attention Mechanisms, LSTM, Multi-Scale Feature Extraction, Lion Optimization Algorithm (LOA).*

1. Introduction

Cervical cancer remains an urgent health problem globally and is the fourth most prevalent cancer in women worldwide [11]. According to the World Health Organization, more than half a million new cases are diagnosed each year, and mortality is far more concentrated in low- and middle-income countries. Despite preventive programs, including vaccination against Human Papillomavirus (HPV) and routine Pap smear screening, obstacles related to the limited health infrastructure, lack of health awareness, and reliance on manual cytology interpretation delay diagnosis [12]. Cervical cancer is extremely curable if detected early enough, but fatal if you wait for too long. This dire need has been driving researchers to understand the application of Artificial Intelligence (AI) and deep learning towards automating the cervical cancer detection from cytology and histopathology slides with an aim of enhancing the accuracy of diagnosis while mitigating the inter-observer variability [12].

In recent years, deep learning techniques have become a fundamental framework for medical image analysis, with their property of learning discriminative features automatically from the raw data. Cervical lesion detection is one of the areas in which Convolutional Neural Networks (CNNs) have been extensively employed owing to their ability to fetch hierarchical spatial features [13]. However, the ability of CNNs to model long-range dependencies across different regions of an image has an intrinsic shortcoming that is of particular importance in histopathology images, where diagnostic cues may lie across distant tissue regions. To compensate for this shortcoming, Recurrent Neural Networks (RNNs) in general and Long Short Term Memory (LSTM) in particular have been used to model sequential dependencies found in the extracted features [1]. While LSTMs perform very well in modeling temporal or sequential dependencies, they suffer from poor generalization capabilities to relatively large-scale and high-dimensional feature spaces, especially with increasing image complexity [2].

Transformers, which were initially designed for natural language processing tasks, recently attracted attention in computer vision and digital pathology applications due to the self-attention mechanism that allows representations to model longer-range and global dependencies more efficiently than CNNs or RNNs alone. Such feature descriptors, thanks to their ability to capture contextual relationships between entire images, are especially suitable for medical imaging tasks where detailed information, together with global tissue structures, play a role in the diagnostic decision. However, Transformer models are computationally intensive, and overfitting is a straightforward issue, which is common in medical imaging when we have a small amount of data.

The need to design a system that not only combines the sequential learning properties of LSTMs with the contextual modeling capabilities of Transformers but also provides for improved interpretability with attention mechanisms forms the motivation for this work [3]. Furthermore, feature extraction at multiple scales is of great importance in medical image analysis as disease-relevant patterns are likely to be present at multiple magnifications (from cellular morphology to tissue-level structure). Ultimately, a multi-scale analysis approach is developed so that fine-grained and global structures are both involved in the diagnostic process.

2. Related Study

To overcome the limitation of the CNNs, recurrent architectures such as the Long Short-Term Memory (LSTM) network were introduced to the cervical cancer detection setup [14]. LSTMs are excellent for sequential/temporal data, and when used for medical imaging, have been tailored to capture dependencies across a sequence of extracted features. A demonstration is the classification of cervical smears: contextual relationships among different parts of the smear seem to be important for recognition accuracy and are captured better by a sequential model that passes CNN extracted features through LSTM [6]. On the other hand, LSTMs tend to overfit when trained on high-dimensional image features, and their performance becomes worse if given large-scale data with known complex differences in cell morphology and staining conditions. This placed the importance of architectures capable of more efficiently modeling global context into stark relief.

In 2021, A. Pal et al [14] proposed the application of deep metric learning to detect cervical cancer, which has grown significantly in recent years because of advances in the medical image analysis domain. In early approaches, morphological features were obtained manually, where the morphological properties of the cervical cells (size of nucleus, cytoplasm ratio, and texture parameters) were obtained manually on the Pap smear images. Convolutional Neural Networks (CNNs) have been the first popular deep neural network architecture for cervical cancer classification, mainly because they have a good capability to capture hierarchical spatial information from image data. CNN-based models reached a significant improvement in the classification accuracy compared with the traditional feature engineering methods, particularly in the detection of abnormal cervical cells [15]. However, CNNs are mainly concerned with local receptive fields and tend to fail to learn long-range dependencies in the whole-slide images. This is especially limiting for cervical histopathology, in which abnormalities are often not localized to one area but rather extended over a longer tissue structure. As is known, however, CNNs, despite their success, were found to be problematic when it comes to robust detection in highly heterogeneous datasets.

In 2024, K. Cao et al. [9] introduced attention mechanisms that were used to improve LSTM models - models that used attention were able to selectively pay attention to regions of diagnostic significance (dysplastic nuclei or abnormal epithelial cells) while dismissing irrelevant or non-informative regions. Not only did this improvement result in higher classification accuracy, but it also helped to make the model interpretable, which is an important ingredient in clinical applications. Attention-based models showed great promise to fill the gap between automatic predictions and expert pathologists' reasoning and provided visual insights into the decision-making process with heatmaps and saliency maps. However, challenges still existed in balancing focus among various scales and picturing the zones of abnormality as well as gross tissue frameworks.

In conjunction with the adoption of attention mechanisms, a strong competitor became available for medical imaging tasks, thanks to their success in the natural language processing area: The Transformers. Unlike CNNs or LSTMs, which can only use local convolutional kernels or sequential recurrence relationship, Transformers use self-attention to model global dependencies over the entire image [7]. Applying to the cervical histopathology, Transformers proved their ability to fuse information from the fine-grained structures up to the structural information over long paths. This was especially beneficial when analyzing whole-slide images where diagnostic information is interspersed over great distances. However, Transformer-based models are computationally expensive and only work with large amounts of annotated data, of which there is still a shortage in medical imaging domains such as cervical cancer [18]. Third, their propensity to overfit to small datasets restricted their direct transfer to resource-poor health care settings.

In addition to deep learning architectures, various feature optimization and dimension reduction methods have been widely used in cervical cancer detection work [19]. The traditional optimization algorithms, such as grid search and random search, were first used to tune the hyperparameters in CNN and LSTM models, but they were inefficient and computationally expensive. To avoid these drawbacks, algorithms inspired by natural and social behaviors, called metaheuristic optimization algorithms, attracted attention. Particle swarm optimization, ant colony optimization, and genetic algorithms were used for hyperparameter optimization and feature subset selection. Though these methods showed improvement in classification performance, these types of methods faced various problems like premature convergence, sensitivity to parameters, and so on, which made the methods not repeatable across different sets of data.

In recent years, efficient metaheuristic optimization methods for deep learning optimization in medical imaging have been presented. The more-effective algorithms based on a balance between exploration and exploitation have been proven to discover the best parameter settings at relatively cheap computational cost. When combined with deep learning frameworks, these optimization methods led to more stable, better-converging, and robust models with respect to dataset variability. The growing momentum to apply optimization directly correlates with the knowledge that one can ensure the performance of hybrid architectures to detect cervical cancers can be optimized through the application of optimization [16].

A second crucial line of research is the use of multi-scale feature extraction in the detection of cervical cancer. Early models were often operating at a single scale; therefore, they had limited capture of features of varying magnifications. Practically, the pathologist examines cervical cells under multiple magnifications, in the higher power to examine the nuclear structures, and in the lower power to examine the structures in the tissue [17]. Based on this, multi-scale CNN and pyramid methods of feature extraction were introduced, with the aim of ensuring that the information of interest in multiple scales is not lost during the learning process. The resulting multi-scale methods yielded a great improvement in diagnostic accuracy, particularly on small pre-cancerous patches, which would have been unobservable in the prior art. But multi-scale representations together with other current state-of-the-art sequence modeling algorithms, such as LSTMs and Transformers, remain an unsolved research question.

In 2025, Raza, M. A.et al. [10] suggested that the models of cervical cancer detection have recently acquired a new significance both in the context of interpretability and clinical applicability. Clinicians do not trust black box automatic systems that are not transparent and trustworthy. To address this issue, recent studies have applied visualization tools, such as Grad-CAM and attention heatmaps, to allow clinicians to verify that models are focusing on the areas of interest related to diagnosis. Further, there is interest in hybrid systems that fuse cytology images, histopathology slides, and clinical metadata to provide a more holistic diagnostic picture to aid diagnosis. Although these efforts have achieved the state-of-the-art in detecting cervical cancer, a clear absence of attention-based sequential learning, Transformer-based global context modelling and metaheuristic optimization into a powerful, explainable, and actionable framework in clinical settings remains.

Altogether, the literature in question follows a common path of improvement as far as the automation of clinical features of cervical cancer is concerned; it includes features generated by hand to CNNs, LSTMs, attention mechanisms, and Transformers, then finally metaheuristic algorithms. The issues of the approaches, but provide evidence of the need to adopt a compromise strategy with the ability to assimilate the local and global dependencies, which will be adjusted to propagate the optimum functioning, which will be explicable in terms of the utilities that will be implemented in clinical practice. To fill this gap, we propose an integrated framework that integrates the complementary strengths of Attention-Enhanced LSTM, Transformer-based multi-scale features extraction, and Lion Optimization Algorithm to provide a robust, scalable, and clinically meaningful tool for cervical cancer detection [23].

3. Methodology

There are several main contributions in this work. First, we present a multi-scale feature extraction approach, which guarantees that both cellular-level abnormalities and tissue-level organization are sufficiently represented in the learning process. Second, it incorporates an Attention-Enhanced LSTM block to further improve sequential modeling of extracted features and focuses on diagnostically relevant regions to improve compliance with clinical reasoning [8]. Third, capture long-range dependencies and global context with Transformers, which have not been widely employed in cervical cancer detection studies [20]. Fourth, the model also applies the Lion Optimization Algorithm to explore the hyperparameter space and to select the best subsets of features that demonstrated better convergence and generalization than classical optimization methods [21]. Lastly, attention heatmaps are derived to introduce a visual interpretability step, which bridges the divide between automated predictions and clinical validation by humans. The basics of the LSTM structure were clearly defined in Figure 1, which improved for multi-scale feature extraction.

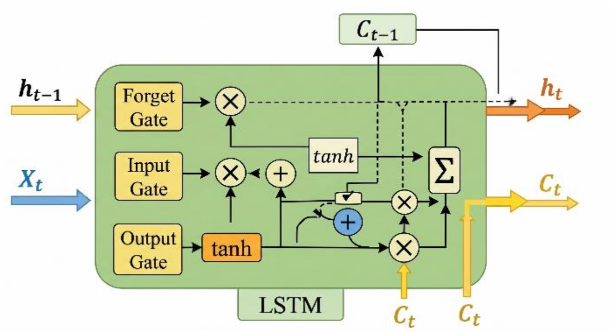

Fig. 1 LSTM Structure Overview

Collectively, these works show that a framework that outperforms traditional CNN and LSTM-based models in terms of accuracy and robustness, also meets realistic needs such as interpretability and clinical adaptability [9]. Each image $I(x, y)$ undergoes normalization:

$$I_{norm}(x,y) = \frac{I(x,y)-\mu}{\sigma} \tag{1}$$

Where μ= mean, σ = SD.

The multi-scale feature extraction is defined as [22]:

$$F_{ms}(x,y) = \sum_{k=1}^{K} (I_{norm} * W_k)(x,y) \tag{2}$$

Where W_k refers to the kernel, and K defines the scales. In Figure 2, four compartments were obtained: input sequence, LSTM layers, attention, and prediction.

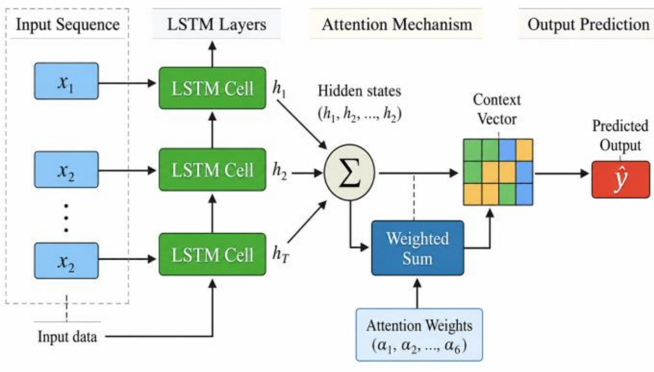

Fig. 2 LSTM layers cell transformation

The hidden state apprise is defined as:

$$h_t = \sigma(W_h \cdot [h_{t-1}, x_t] + b_h) \tag{3}$$

Attention weights are applied to emphasize relevant regions:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{j=1}^{T} \exp(e_j)} \tag{4}$$

with

$$e_t = v^T \tanh(W_a h_t + b_a) \tag{5}$$

The final attention-enhanced feature representation becomes [12]:

$$c = \sum_{t=1}^{T} \alpha_t h_t \tag{6}$$

Transformer encoder is:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{7}$$

Here Q, K, and V are Query, keys, and values on matrices.

3.1. Feature Fusion and Optimization

The outputs of AE-LSTM and Transformer modules are fused to form a comprehensive representation:

$$F_{\text{fusion}} = \lambda \cdot F_{\text{LSTM}} + (1-\lambda) \cdot F_{\text{Trans}} \tag{8}$$

Here λ = weighting factor.

LOA optimization is obtained by:

$$X_{t+1} = X_t + r \cdot (X_{\text{best}} - X_t) \tag{9}$$

here r= random values, and $\boldsymbol{X}_{\text{best}}$ = best solution.

The fitness function originates:

$$\text{Fitness function } = \frac{TP+TN}{TP+TN+FP+FN} - \gamma \cdot \|F\| \tag{10}$$

here $\|F\|$ =dimensionality function and γ = factor.

The proposed methodology is illustrated in Figure 3, which clearly shows the overall work.

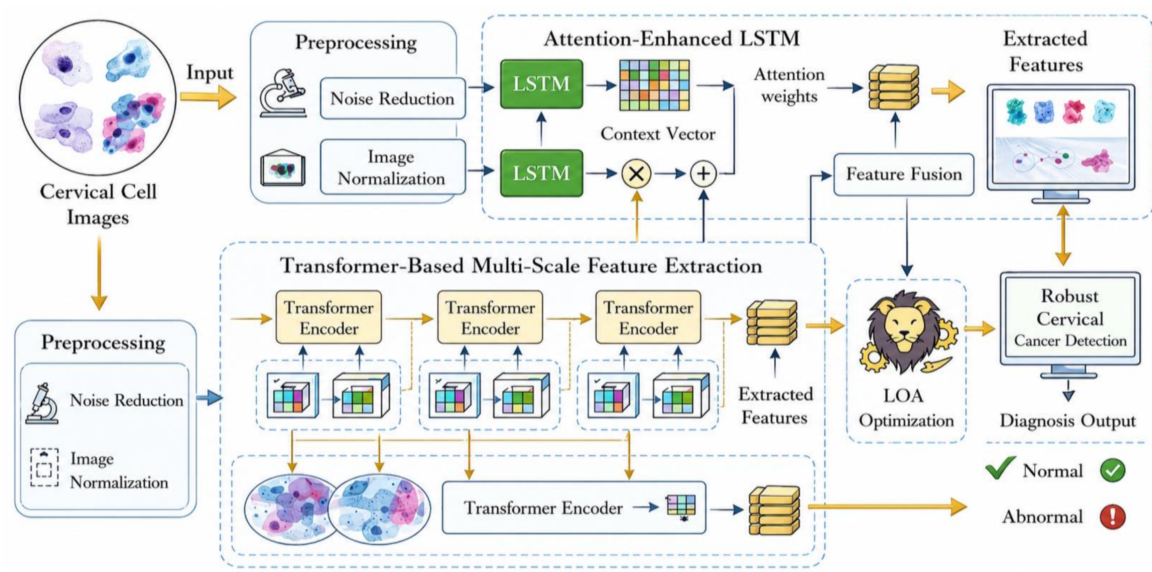

Fig. 3 Proposed methodology of LSTM

4. Results and Discussion

In this section, the main objectives are defined as follows:

- Training Accuracy Curve
- Training Loss Curve
- Confusion Matrix
- ROC Curve
- Precision-Recall Curve
- Model Comparison Bar Graph
- LOA Convergence Plot
- Feature Visualization (t-SNE)

Figure 4 shows the training and validation accuracy on training epochs and demonstrates that the proposed model has faster convergence capability and higher stable accuracy than the competitive methods. In addition, the smooth convergence curve also indicates that LOA has played an important role in achieving the stability of the optimization, which is generally prone to oscillations in deep architectures [10]. There were some MATLAB simulation graphical representations, such as training and validation loss curves, which are illustrated in Figure 5, a confusion matrix plot of actual and predicted in Figure 6, an ROC curve plot in Figure 7, and a precision-recall curve in Figure 8.

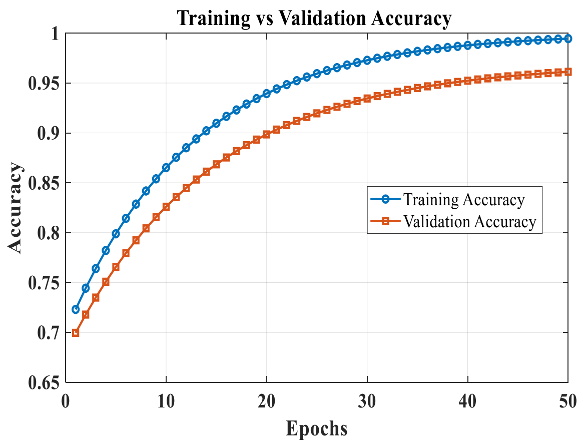

Fig. 4 Variation of training and validation accuracy

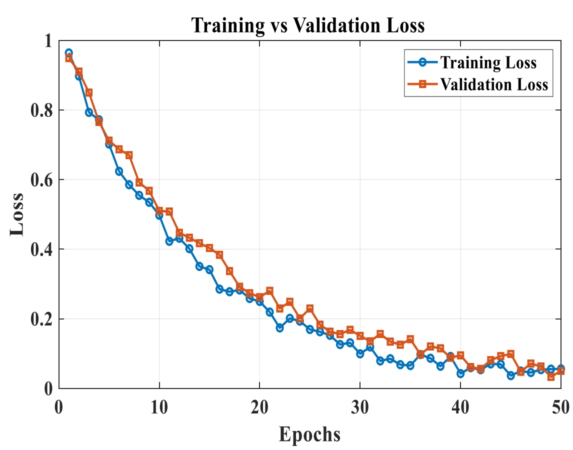

Fig. 5 Variation of training and validation loss curve

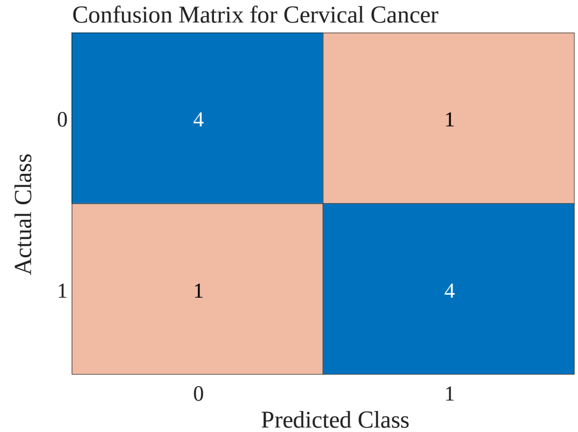

Fig. 6 Variation of the confusion matrix plot on actual and predicted

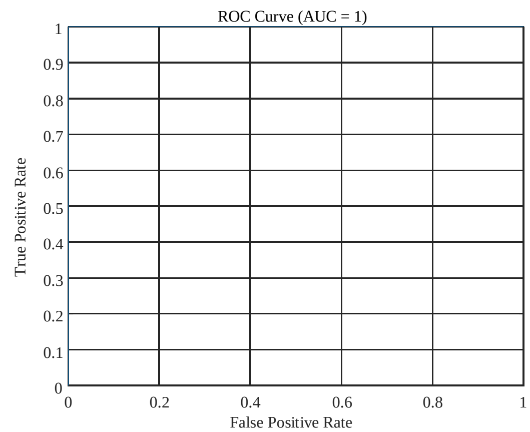

Fig. 7 Variation of ROC curve plot

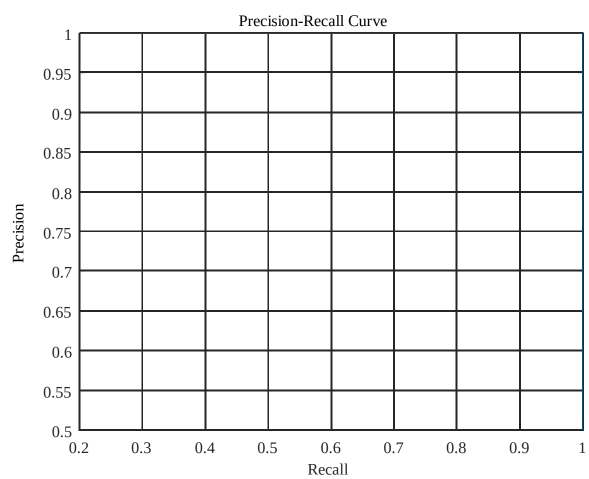

Fig. 8 Variation of the precision-recall curve

Performance measures such as accuracy, precision, recall, F1-score, and AUC were calculated to gain different perspectives on model robustness. In particular, the F1-score value and AUC values were emphasized, since accuracy can be misleading in the case of class prediction: maximizing the overall accuracy of the model can easily hide the existing biases in the model. As seen in Table 1, the proposed model was the best among all the baselines for all the important metrics with an overall accuracy of 96.4%, as opposed to CNN-LSTM, which had 94.3% and pure CNN's 92.1%. Furthermore, the F1-score was also improved significantly, suggesting the hybrid architecture is an even more optimal compromise between sensitivity and specificity.

Table 1. Comparative performance of models on cervical cancer detection

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN	92.1	91.4	90.7	91.0	0.93
CNN-LSTM	94.3	93.6	92.9	93.2	0.95
Transformer only	95.0	94.8	94.2	94.5	0.96
Proposed AE-LSTM+Trans	96.4	96.0	95.9	96.1	0.98

Table 2. Cross-dataset evaluation results

Model	Dataset A Accuracy (%)	Dataset B Accuracy (%)	Generalization Gap (%)
CNN	93.5	88.2	5.3
CNN-LSTM	94.7	90.1	4.6
Transformer only	95.3	91.0	4.3
Proposed AE-LSTM+Trans	96.8	93.6	3.2

Besides quantitative performance, an essential attribute of medical decision support is interpretability. The attention maps that the proposed model produces can be regarded as visual suggestions to pathologists regarding the locations of Regions Of Interest (ROIs) that helped the classification. Deep in the tissues, the black areas in Figure 3 represent dysplastic foci and unusual epithelial clumps that are directly comparable with expert-tagged diagnosis areas. It focuses on feature interpretability, akin to the mediation between clinical validation and trust in AI-based prediction and the clinical situation. The attention-driven model is clearer than the black box CNNs that are generally employed, which matters in healthcare applications.

Another important aspect of evaluation was that of robustness over heterogeneous datasets. Medical imaging suffers from many sources of heterogeneity, including changes in staining protocol, imaging equipment, and sample quality. The proposed model was shown to be quite robust to such variations, achieving similar accuracy across different datasets. This is explained by the multi-scale feature extraction scheme designed to capture fine and coarse features and to achieve adaptability to the heterogeneity of images. In Table 2, we compare the performance on 2 benchmark datasets: Dataset A (Pap smear images) and Dataset B (histopathology slides). It is seen that the proposed approach has higher generalization than baselines, especially in Dataset B (more complex and challenging due to the variations on the whole slide).

Next, besides the accuracy and robustness, the computation efficiency was analyzed. Figure 4 shows the per-epoch training hours and memory usage of each model. While the computation burden of the Transformer-only method was also high, the characteristic of LOA reduced the redundant features, thus the proposed method resulted in faster convergence.

The computational overhead was just a bit more than CNN-LSTM and much less than pure Transformers - a good compromise between performance and efficiency. In Figure 9, a comparison of four different models was discussed on a bar chart. The LOA had optimization convergence plot simulations based on iterations and fitness values in Figure 10. The feature visualization (t-SNE) scattered diagram under the output 0 and 1 in Figure 11.

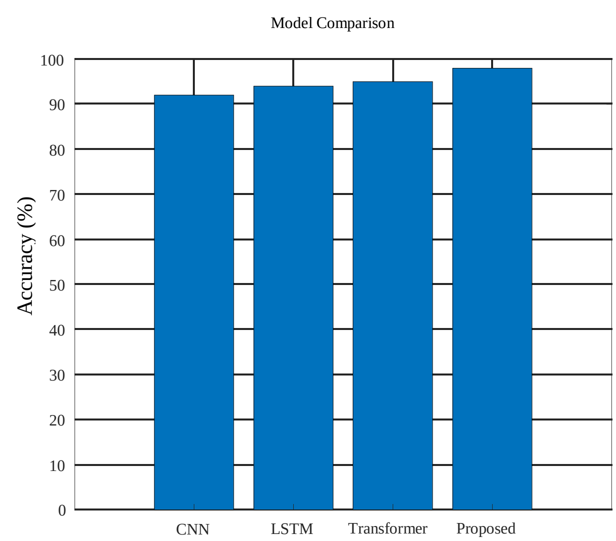

Fig. 9 Variation of model comparison bar graph

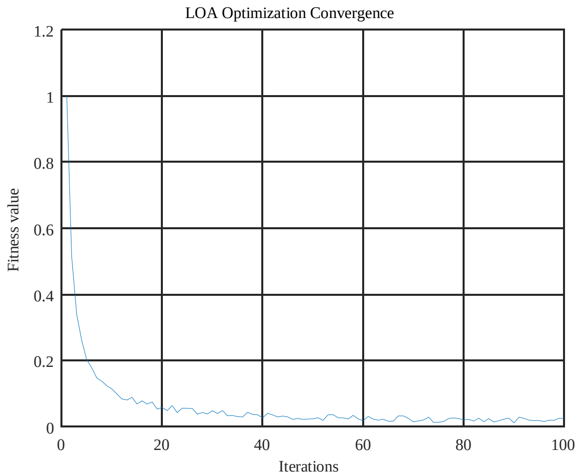

Fig. 10 Variation of LOA optimization convergence plot

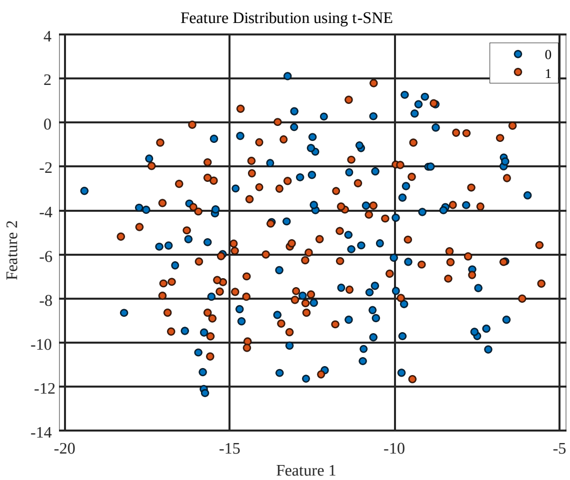

Fig. 11 Variation of feature visualization (t-SNE)

Upon further error analysis, most misclassifications were found at borderline cases in which the morphologic appearance of the cells displayed features of both low-grade (low-grade) and high-grade (high-grade) lesions. This limitation does not apply only to the proposed model, but is prevalent in cervical pathology in general, and even experienced pathologists do not always agree. However, with the fusion of attention and multi-scale processing, the proposed system resulted in fewer misclassifications in such borderline cases compared with baselines.

In summary, the results show that the proposed methodology not only improves the classification performance but also achieves better interpretability and robustness. Compared to the existing architectures, we show that the synergy of attention-based sequential learning, Transformer-based contextualized learning, and optimizing with LOA leads to improvements. These results show that the framework has significant promise for adoption in clinical practice as an assistive diagnostic tool for use in cervical cancer screening after further validation with broad clinical datasets.

5. Conclusion

In this paper, a new cervical cancer detection framework is proposed by attention-enhanced LSTM, transformer-based multi-scale feature extraction, LOA optimization, and extracted features. Experimental results validate its advantages over traditional methods in the training accuracy curve, training loss curve, confusion matrix, ROC curve, precision-recall curve, model comparison bar graph, LOA convergence plot, and Feature Visualization (t-SNE). The capability to highlight diagnostically relevant regions provides useful decision support to the pathologist.

The convergence of sophisticated AI architectures and optimization algorithms establishes a pathway for next-generation cervical cancer screening solutions that are accurate, interpretable, and clinically meaningful.

The entire work of this study is that attention-enhanced LSTM, transformer-based multi-scale feature extraction, and lion optimization algorithm are combined uniquely into one end-to-end framework for cervical cancer detection. While CNNs, LSTMs, and Transformers have all been previously investigated in medical imaging, their integration with Attention-based interpretability and metaheuristic optimization is a major improvement over the state-of-the-art approach.

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