Hybrid Graph Attention And Temporal Deep Learning Framework For Early Prediction Of Cervical Cancer Risk

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Abstract- *Cervical cancer remains one of the leading causes of cancer-related deaths among women worldwide. Early identification of high-risk individuals is essential for timely intervention and improved survival rates. Traditional machine learning and deep learning approaches often fail to capture complex feature relationships, temporal dependencies, and provide adequate interpretability. This study proposes an Explainable Hybrid Graph Attention Network–Temporal Deep Learning (GAT-TDL) framework for cervical cancer risk prediction using structured clinical data. The framework integrates Graph Attention Networks (GAT) for modeling feature dependencies, Bidirectional Gated Recurrent Units (BiGRU) for temporal learning, and a lightweight 1D Residual CNN for feature refinement. To enhance transparency and clinician trust, Explainable AI (XAI) techniques including SHAP and Integrated Gradients are incorporated. The model was evaluated using the UCI Cervical Cancer dataset and achieved an accuracy of 96.58%, sensitivity of 95.65%, specificity of 97.52%, and AUC-ROC of 98.64%. Experimental results demonstrate that the proposed framework outperforms conventional machine learning models while providing interpretable and clinically meaningful predictions.*

Keywords: Cervical Cancer Prediction, Graph Attention Network (GAT), BiGRU, Explainable Artificial Intelligence (XAI), Deep Learning, SHAP, Integrated Gradients, Risk Assessment, Healthcare Analytics.

I. INTRODUCTION

Cervical cancer is a significant public health concern affecting millions of women globally. Despite advancements in screening methods such as Pap smear and HPV testing, delayed diagnosis remains a major challenge, especially in low-resource healthcare settings. Early detection plays a critical role in reducing mortality and improving treatment outcomes.

Artificial Intelligence (AI) and Deep Learning (DL) have emerged as promising technologies for disease prediction and diagnosis. However, many existing approaches focus primarily on predictive performance and often overlook the importance of modeling complex clinical relationships and providing explainable results. Medical decision-making requires not only accurate predictions but also transparency regarding how those predictions are made.

To address these challenges, this research introduces an Explainable Hybrid GAT-TDL framework that combines graph-based feature learning, temporal sequence modeling, and explainable AI techniques. The proposed system aims to improve prediction accuracy while ensuring interpretability and clinical reliability.

II. LITERATURE REVIEW

Several studies have explored the application of AI and deep learning techniques for cancer prediction and diagnosis.

Multi-Omics Integration Using Graph-Based Learning

Graph-based learning approaches have been utilized to integrate diverse biological datasets such as genomics, transcriptomics, proteomics, and epigenomics. These methods effectively model complex biological interactions and improve disease prediction accuracy through Graph Neural Networks (GNNs).

Spatio-Temporal Attention Networks

Spatio-temporal attention networks combine spatial feature extraction and temporal sequence learning to forecast cancer risk. Attention mechanisms enable the model to focus on the most relevant features and time intervals, improving prediction performance and interpretability.

Explainable Deep Learning for Cervical Cancer Detection

Deep learning techniques such as Convolutional Neural Networks (CNNs) have shown promising results in cervical cancer diagnosis from medical images. Explainable

AI methods including LIME, SHAP, and Grad-CAM have been integrated to improve transparency and clinical trust.

Hybrid GAT-LSTM Models

Hybrid Graph Attention Network (GAT) and Long Short-Term Memory (LSTM) architectures have been developed for medical time-series classification. These models effectively capture both feature dependencies and temporal patterns, leading to improved disease prediction performance.

Temporal Graph Networks with Explainability

Temporal Graph Networks (TGNs) model patient health records as evolving graphs and incorporate attention mechanisms for disease risk prediction. Their ability to capture dynamic patient interactions and provide explainable outputs makes them highly suitable for healthcare applications.

Although these approaches have demonstrated encouraging results, challenges remain regarding computational complexity, scalability, robustness to noisy data, and comprehensive explainability. The proposed GAT-TDL framework aims to address these limitations.

III. METHODOLOGY

Dataset

The study utilizes the UCI Cervical Cancer Dataset, which contains demographic, behavioral, and clinical risk factors including age, pregnancies, smoking habits, contraceptive use, sexually transmitted diseases, and diagnostic test results.

Data Preprocessing

The preprocessing stage includes:

- Missing value imputation
- Feature normalization
- Categorical feature encoding
- Class balancing using SMOTE
- Noise removal and outlier handling

These steps ensure high-quality data for model training.

Graph Construction

Clinical features are represented as graph nodes, while relationships between features are represented as edges. Connections are established using medical knowledge and statistical correlations, allowing the model to explicitly capture inter-feature dependencies.

Graph Attention Network (GAT)

The GAT module learns adaptive attention weights between connected features. This enables the model to identify the most influential risk factors and capture higher-order feature interactions.

Temporal Learning Using BiGRU

A Bidirectional Gated Recurrent Unit (BiGRU) processes sequential patient information in both forward and backward directions, enabling comprehensive temporal pattern learning and disease progression modeling.

1D Residual CNN

The extracted graph and temporal features are further refined using a lightweight 1D Residual CNN. This module suppresses noise, improves feature representation, and enhances model generalization.

Classification Layer

The refined features are passed through fully connected layers to generate cervical cancer risk predictions. The model supports both binary and multi-class classification tasks.

Explainable AI Module

To improve transparency and clinical acceptance, SHAP is used for global feature importance analysis, while Integrated Gradients provide patient-specific explanations.

Evaluation Metrics

Model performance is evaluated using:

- Accuracy
- Sensitivity
- Specificity
- Precision
- F1-Score
- AUC-ROC

IV. RESULTS AND DISCUSSION

The proposed GAT-TDL framework demonstrated excellent predictive performance on the UCI Cervical Cancer dataset.

Metric	Value
Accuracy	96.58%
Sensitivity	95.65%
Specificity	97.52%
Precision	97.47%
F1-Score	96.55%
AUC-ROC	98.64%

The ROC analysis achieved an AUC value of 0.9904, indicating excellent discrimination between high-risk and low-risk patients.

The confusion matrix showed:

- True Positives: 159
- True Negatives: 157
- False Positives: 4
- False Negatives: 2

These results indicate strong classification performance and clinical reliability.

Comparative analysis against baseline models such as Logistic Regression, Random Forest, Gradient Boosting, Support Vector Machine, and K-Nearest Neighbor demonstrated superior and more balanced performance of the proposed framework.

Explainability Analysis

SHAP analysis identified the most influential predictors as:

- Hinselmann test result
- Cytology result
- Schiller test result
- HPV diagnosis history
- Smoking behavior
- Hormonal contraceptive use

Integrated Gradients provided patient-specific explanations by highlighting risk factors contributing to individual predictions. This improved transparency and strengthened clinician confidence in the model.

Overall, the integration of graph learning, temporal modeling, and explainability significantly enhanced both predictive performance and interpretability.

V. CONCLUSION

This study presents an Explainable Hybrid GAT-TDL framework for cervical cancer risk prediction. The proposed architecture effectively integrates Graph Attention Networks, Bidirectional GRUs, and Residual CNNs to capture feature relationships, temporal dependencies, and refined clinical patterns. The inclusion of Explainable AI techniques such as SHAP and Integrated Gradients enhances model transparency and clinical trust.

Experimental results demonstrate that the framework achieves high predictive accuracy, sensitivity, specificity, and AUC-ROC while outperforming conventional machine learning approaches. Furthermore, its lightweight architecture and interpretability make it suitable for deployment in real-world healthcare environments, particularly for early screening and risk assessment.

Future work may focus on integrating multi-modal healthcare data, validating the model on larger clinical datasets, and developing real-time clinical decision support systems.

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