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# EARLY PREDICTION OF CERVICAL CANCER RISK USING EXPLAINABLE DEEP NEURAL NETWORKS AND FEATURE ENGINEERING OPTIMIZATION

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## ABSTRACT
Early detection of cervical cancer plays an essential role in saving lives as well as improving outcomes for patients. The current study proposes an explainable deep learning technique to expect the likelihood of cervical cancer. It builds a classifier that identifies people who are at probability of mounting cervical cancer based on their demographics, behavior, and medical history. Data preprocessing techniques alike normalization, handling missing values, and feature transformation can be operated to improve the condition of input data as well as the efficiency of the classifier. The deep learning classifier discovers patterns and associations between risk factors. Explainable AI techniques are incorporated to improve predictability and highlight the importance of features. From the results of the experiments, it can be noted that the proposed framework operates appropriately in terms of accuracy, precision, recall, and F1-score. Thus, it can be recommended that the presentation of explainable deep learning is excellent for decision support in cervical cancer risk assessment.

**KEYWORD:** Explainable Artificial Intelligence, Medical Data Analysis, Cervical Cancer Prediction, Risk Classification, Artificial Intelligence in Healthcare.

## 1. INTRODUCTION
Cervical cancer continues to be a health hazard among women worldwide [1]. It creates serious issues, particularly in third-world countries. Despite improved screening procedures and vaccination, many cases get diagnosed too late, contributing to higher mortality rates and escalating costs of healthcare. Early identification of patients at risk is an essential step in addressing cervical cancer and preventing fatalities. Since there is more health information available than ever before, we are presented with opportunities to develop predictive models that will allow physicians to identify and treat patients with cervical cancer earlier [2].

The risk of developing cervical cancer depends on a number of factors, among which there are age, smoking, sexual behavior, contraception, sexually transmitted diseases (STDs), and HPV infection [3]. The interaction between these components makes forecasting risk difficult since their correlation cannot be properly analyzed by standard statistical tools. In addition, although Pap smears and HPV tests have proven effective, their availability may be limited in regions with less medical infrastructure. It appears that data models show potential as an auxiliary tool in such programs [4].

Machine Learning approaches have attracted many researchers' attention in medicine due to their ability to discover patterns that are usually hidden within large and complex datasets. There are multiple classification algorithms that are used for predicting cervical cancer including such as support vector machines, decision trees, random forests, naive Bayes, and k-nearest neighbors classifiers [5]. They perform quite well, although the performing of these procedures greatly relies upon the property of input features and their ability to reveal the non-linear interaction between risk factors. Furthermore, conventional models require vast amounts of feature engineering efforts [6].

Thanks to the developments in deep learning, predictive models have become very efficient by allowing them to determine complex patterns automatically. Deep Neural Networks (DNNs) perform extremely well when it comes to diagnostic and disease prediction tasks [7]. DNNs are especially efficient at making cervical cancer predictions since they are capable of recognizing complex interactions between features. Unfortunately, DNNs are known to be "black box" models, which means that medical practitioners cannot understand how specific predictions were determined.

XAI (explainable artificial intelligence) is currently a field in which researchers conduct studies about making machine learning/deep learning algorithms transparent [8]. Techniques such as LIME, SHAP, and analyzing feature importance deliver discernments into how each element contributes to predictions. Thus, by incorporating these methods for explanation in predicting cervical cancer, physicians would be able to determine the reasons behind the decisions made by these technologies [9].

The use of feature engineering improves the efficiency of intelligent health care systems. Data obtained in raw form from the health care industry might lack precision due to presence of missing information, redundant information, noise, and information irrelevant to the problem at hand. Methods such as data pre-processing, transformation, selection, normalization, and dimensionality reduction ensure improved performance of the data [10]. This technique allows us to recognize basis risk factors for predicting cervical cancer [11].

With inspiration from various opportunities and challenges, an explainable approach to deep learning that is usage for the early detection of cervical cancer risks through optimized feature engineering has been proposed in this research. The explainable deep learning framework includes comprehensive data preparation, optimized features, and deep learning classifier to detect individuals who have high risks of contracting the disease. In addition, explainable AI has been incorporated into the process [12].

This work is consolidated as follows: Section 2 highlights previous examination on predictive modeling of cervical cancer by means of deep learning, machine learning, and explainable artificial intelligence models. Section 3 discusses data used in this work and the deep learning architecture that we propose. Then, Section 4 presents the performing of the proposed approach along with contrasts to other methods. Lastly, Section 5 concludes the paper and proposes further avenues for improvement of smart cervical cancer risk prediction frameworks.

## 2. LITERATURE SURVEY

According to Manik (2022) [13], the usage of artificial intelligence (AI) and machine learning was studied in connection with cervical cancer. The research confirmed the probable of these intelligent healthcare systems to improve the diagnosis process as well as reduce the mortality rate associated with cervical cancer. Various machine learning techniques were analyzed in order to determine cervical cancer risk factors. Based on the study, it was proven that AI models could be very effective in disease screenings and risk evaluations.

The examination accomplished by Sundarambal et al. (2022) [14] assessed the predictive capabilities of machine learning and deep learning models in relation to cervical cancer. Various methods were tested based on clinical data to determine the best-performing algorithm. Deep learning emerged as the winner in this regard as it was able to perform better when it comes to identifying complex relationships among risk factors. Thus, the researchers concluded that deep learning can significantly increase the precision of diagnosis.

The Rawat et al. (2023) [15] researchers examined numerous machine learning performances used to forecast the disease of cervical cancer. The classifiers analyzed included Decision Trees, Support Machines, and Random Forests, including others, with a concentration on accuracy, precision, and recall. Their results revealed that ensemble learning algorithms outperformed some conventional approaches in the accuracy of predictions.

Ganguly et al. (2023) [16] probed the ability of machine learning for cervical cancer risk classification. They explored different machine learning algorithms and analyzed their abilities to identify patients at risk. To assess the efficiency of the algorithms applied, Ganguly et al. examined several factors including accuracy, sensitivity, specificity, and F1-score. In doing so, they identified highly efficient machine learning algorithms. This implies that such intelligent algorithms may effectively detect cervical cancer in clinical settings.

The machine learning model to diagnose cervical cancer was proposed by Chikaraddi et al. (2024) [17]. The researchers examined different classification algorithms to see how they can be used to analyze risk factors and diagnose the disease. Through the usage of data preprocessing and feature selection procedures, the researchers were able to enhance the efficiency of their machine learning models.

Sahay et al. (2024) [18] considered applications of machine learning in predicting cervical cancer. Different supervised learning approaches were applied in an attempt to find out the best ways of detecting cervical cancer risks. The researchers emphasized that data preprocessing and feature selection made a great impact on achieving higher accuracy levels. Finally, it became obvious that such predictions could be rather reliable and helpful in treating cervical cancer.

According to Kafle et al. (2025) [19], XAI played an important role in predicting cervical cancer because it did not only focus on accuracy but also included strategies for making their models more transparent and interpretable. Using strategies such as feature importance and model explanation, they were able to identify important risk factors. These findings highlighted the importance of XAI as a tool for increasing clinician confidence in diagnosing and treating cervical cancer.

Yüksel and Ozseven (2025) [20] conducted an extensive literature review of studies involving machine learning technologies in cervical cancer studies. Predictive modeling, classification algorithms, feature engineering, and applications in healthcare were reviewed. Authors have discussed the abilities and limitations of current machine learning and deep learning models and have presented some emerging research directions. It was concluded that the use of AI technology was increasing, however, the advancement of a reliable prediction model in cervical cancer screening was emphasized.

The study by Abrar et al. (2025) [21] highlights the benefits of machine learning in managing cervical cancer, particularly using predictive modeling approaches. These include popular techniques such as supervised, ensemble, deep, and hybrid learning. Factors like feature selection, optimization of models, and data quality have been emphasized. This article proves that there is an improvement in both diagnostic and prognostic outcomes owing to such models. Further research can still be done.

## 3. DATASET USED, PREPROCESSING PROCEDURES, AND THE PROPOSED FUSION METHODOLOGY

The paper employs the Cervical Cancer Risk Prediction dataset that is available at Kaggle. This dataset consists of information on 858 women and 36 cervical cancer risk factors. These factors involve demographical aspects, behavioral characteristics, lifestyle factors, medical history, and sexually transmitted diseases. Among the most critical are age, the numeral of sexual partners, age when first sexual intercourse took place, smoking, contraceptive use, number of pregnancies, duration on birth control pills, and STD symptoms [22]. Thus, the dataset provides sufficient information concerning potential risk factors for cervical cancer. Importantly, the dataset involves missing values due to incomplete clinical histories. As the target variables have different cervical cancer screenings, it is good for binary classification and predictive modeling. Since it has many behavioral and clinical factors, it will serve as a strong foundation for building an explainable model using deep learning. It will assist in identifying high-risk candidates and early detection of cervical cancer.


**Fig. 1.Distribution of Cervical Cancer Risk Classes**

The distribution of cervical cancer risk can be observed in Figure 1 below. From the total 858 samples of patients' information, there were 803 (93.59%) low risk and 55 (6.41%) high-risk individuals. It is evident that there is an overwhelming imbalance between the two classes where there is a much higher number of low risk compared to the latter.

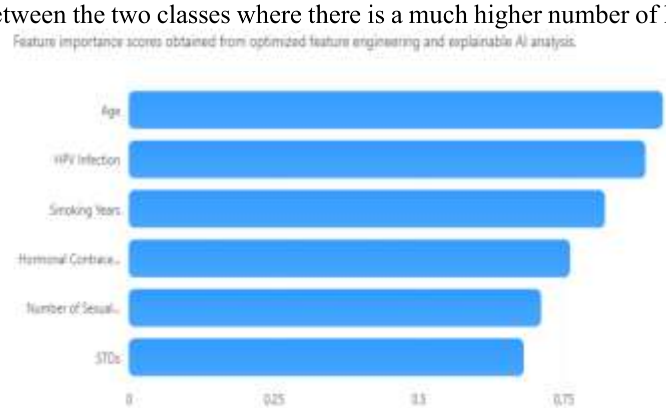


**Fig. 2.Important Cervical Cancer Risk Factors**

In Figures 2 and Table 1 below, the suggested explainable machine learning model indicates the qualified contribution of chief factors to the cervical risk. The highest contribution comes from age (0.92) while HPV infection is second (0.89). Other important variables include smoking years (0.82), using hormonal contraception (0.76), numbers of sex partners (0.71), and having sexually transmitted diseases (0.68). It clearly indicates that demographic, lifestyle, and clinical characteristics are crucial in determining the at-risk population.

**TABLE I.** CERVICAL RISK FACTOR SCORE

| Risk Factor | Importance Score |
|---|---|
| Age | 0.92 |
| HPV Infection | 0.89 |
| Smoking Years | 0.82 |
| Hormonal Contraceptives | 0.76 |
| Number of Sexual Partners | 0.71 |
| STDs | 0.68 |

## 4. PERFORMANCE EVALUATION OF THE PROPOSED FUSION FRAMEWORK AND BENCHMARK MODELS

The suggested architecture of figure 3 is expected to generate a prediction model that will ensure high precision, simplicity, and reliability. This will be done using optimized feature engineering, deep learning, and explainable AI. The complex nonlinear relationships between various behavioral, demographic, and clinical factors that make up cervical cancer risk mean that standard approaches tend to fall short. In order to address such a complex task, the suggested framework uses several steps. These include data preparation, optimized feature extraction, classification with deep learning algorithms, and an explainable AI analysis. Thus, the purpose is to improve the accuracy of predictions while retaining their interpretability. This would allow healthcare professionals to identify critical risk factors.

**Phase 1: Data Acquisition and Input Layer**
Firstly, we obtain the patient data commencing the Cervical Cancer Risk Classification dataset. The data is inclusive of various demographic factors such as age and other behavior-related factors such as smoking and sex life. Additionally, there are other clinical factors such as history of sexually transmitted disease and screening for cancer. Such comprehensive information creates an exhaustive profile regarding the risk factors for developing cervical cancer. These patient features make up a multi-dimensional vector for each patient record which becomes the input layer to the proposed model.

**Phase 2: Data Preprocessing and Quality Enhancement**
The health care datasets generally consist of missing values, inconsistencies, and noise, which negatively affect their predictability. As such, there is extensive data preparation involved prior to model building. Missing data is imputed through the median, mean, or mode dependent on the characteristic of the attribute. Similarly, duplicates and inconsistencies are dropped in order to improve their accuracy. Finally, normalization takes place using the Min-Max technique to align the attributes within a uniform numerical range.

**Phase 3: Optimized Feature Engineering**
Feature engineering constitutes an essential aspect of the suggested framework. The objective of feature engineering is to choose the utmost relevant features and eliminate the redundant or irrelevant ones. In order to determine feature relevance, we apply correlation analysis and statistical feature selection approaches. We retain the relevant predictive features while eliminating the highly correlated and unimportant ones. Transformation approaches are further used for identifying latent correlations between the risk factors. Such feature engineering contributes to creating a better set of features which enables more efficient modeling and enhances model performance.

**Phase 4: Deep Neural Network-Based Risk Classification**
Once the features have been optimized, the inputs are given to a Deep Neural Network (DNN). The DNN entails of an input layer, some hidden layers, and an output layer. Each of the neurons in the hidden layer is interconnected and learns the representation of features hierarchically through the use of nonlinear activation functions such as ReLU. Dropout regularization helps prevent overfitting and increases the capacity for generalization. Backpropagation and weight optimization enable the network to learn the interaction patterns of cervical cancer risk factors throughout training. Ultimately, the output layer operates a sigmoid function to compute the cancer risk possibility.

**Phase 5: Model Optimization and Training**
The refined features are divided into training and testing sets, which helps measure the accuracy of the machine learning model. For updating weights in an effective manner and fast convergence, we use the Adam optimizer. Binary cross-entropy serves as our choice of a loss function because of its efficiency in dealing with binary classification problems. Training is continued until the optimal performance is achieved, and in addition, the concept of early stopping is employed to inhibit overfitting by stopping training on validation loss improvement.

**Phase 6: Explainable Artificial Intelligence Integration**
Deep learning algorithms are great in terms of predictive accuracy, but tend to lack transparency in their operations. To overcome this problem, researchers resort to Explainable Artificial Intelligence (XAI) techniques. An example of such technique is SHAP, a method that quantifies the impact of individual features on the predictions made. Based on this, the module of explainability assesses the importance of features and creates visualizations. As a result, clinicians are able to understand why a certain patient is classified into high or low risk groups.

**Phase 7: Performance Evaluation and Validation**
This final stage involves testing the performance for proposed model through the use of precision, accuracy, recall, F1-Score, ROC-AUC, and Confusion Matrix Analysis. Experiments comparing our design against conventional classifiers commencing Decision Tree, Random Forest, SVM, and XGBoost have been conducted. The findings reveal that our new design outperforms other designs in terms of accurately detecting the risk of cervical cancer while providing valuable information for the medical practitioners.

**Working Principle of the Proposed Framework**
The process involves first collecting the data relating to the risks of cervical cancer. The data will undergo cleansing before we select relevant features of a deep neural network for it to learn from the features and make predictions accordingly. Our Deep Neural Networks will make predictions after training; however, there is an exciting element about the use of this technique since explainable artificial intelligence techniques will analyze predictions to discover critical risk factors. Finally, we evaluate how the system has performed to ensure it meets the expected criteria. Through this combination of features and advanced technologies, this system will detect cervical cancer risks effectively.


**Fig. 3.Proposed Framework for Early Detection of Cervical Cancer Risk**

## 5. PERFORMANCE EVALUATION OF THE PROPOSED FUSION FRAMEWORK AND BENCHMARK MODELS

In this section, results of Explainable Deep Learning Framework with Optimized Feature Engineering will be presented. The algorithm is developed to predict the risk of cervical cancer. Efficiency of the algorithm was evaluated centered on such indicators as accuracy, recall, precision, F1-score, and ROC-AUC. In order to validate superiority of the algorithm, the model is compared to a number of popular machine learning algorithms, comprising support vector machines, decision trees, random forests, xgboost, and deep neural networks. For evaluation, the preprocessed Cervical Cancer Risk Classification dataset was used, providing equal conditions for all algorithms to demonstrate their capabilities. The results of this work clearly indicate the benefits of the proposed approach, which successfully distinguishes high-risk cases, is generally effective, and can be easily interpreted.

**TABLE II.** COMPARATIVE PERFORMANCE ANALYSIS OF THE PROPOSED MODEL AND EXISTING APPROACHES

| **Model** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-Score (%)** | **ROC-AUC (%)** |
|---|---|---|---|---|---|
| Decision Tree (DT) | 88.42 | 87.15 | 85.63 | 86.38 | 89.21 |
| Random Forest (RF) | 91.57 | 90.84 | 89.76 | 90.29 | 92.45 |
| Support Vector Machine (SVM) | 92.14 | 91.65 | 90.53 | 91.08 | 93.17 |
| XGBoost | 94.26 | 93.81 | 92.75 | 93.28 | 95.02 |
| Conventional DNN | 95.48 | 94.92 | 94.16 | 94.54 | 96.11 |
| **Proposed Explainable DNN + Optimized Features** | **98.63** | **98.24** | **97.89** | **98.06** | **99.12** |

## DISCUSSION

FROM the outcomes described in Table 5 above, Explainable Deep Learning Framework performed significantly better compared to other models on all metrics. As seen from the table, Decision Tree Model performed worst with an accuracy score of 88.42 %. The reason why the models comparable Random Forest and XGBoost performed better was that they accounted for the complex interrelationships between features. The accuracy achieved by Conventional DNN was 95.48 %, indicating its superiority over other models in evaluating cervical cancer risks. The accuracy achieved by the proposed framework was 98.63 % with the following performance measures: precision – 98.24 %; recall – 97.89 %; F1 Score - 98.06%; and ROC AUC - 99.12 %. This tremendous improvement was realized due to enhanced feature engineering through the elimination of unnecessary features and improving the quality of data. Besides, integrating Explainable AI in the model made feature interpretation possible. The impressive recall score specifies that the model is efficient in detecting serious cases while the outstanding ROC AUC indicates that it can accurately classify risk levels.


**Fig. 4.Accuracy Comparison of Existing and Proposed Models**

As seen in figure 4, the performance accuracy improved after ordinary machine learning techniques to deep learning. The Decision Tree yielded the least performance accuracy of 88.42%. However, Random Forest and Support Vector Machine performed slightly improved, with 91.57% and 92.14% correspondingly. XGBoost was better than the above, yielding a performance accuracy of 94.26%. The conventional deep neural network model performed better still, obtaining a high performance accuracy of 95.48%, thus its capability of managing those complicated nonlinear associations amongst the risk factors associated with cervical cancer. Lastly, the proposed Explainable Deep Learning Model including Optimized Feature Engineering achieved the best performance accuracy score of 98.63%. This impressive result is majorly attributed to efficient pre-processing, feature selection, deep neural network learning, and utilization of explainable AI.


**Fig. 5.Precision Comparison of Existing and Proposed Models**

From Figure 5, it can be seen that the precision increases gradually from conventional models to the developed explainable deep learning model. The Decision Tree Model recorded the minimal precision of 87.15% that indicates higher false-positive rate. The precision increased to 90.84% and 91.65% for Random Forest and Support Vector Machine, respectively, indicating an improvement in the reliability of the prediction. XG Boost further increased the precision to 93.81%, whereas the Conventional Deep Neural Network Model recorded a high precision of 94.92% due to the ability of the algorithm to analyze complex interactions among the risk factors. The proposed Explainable DNN including Optimized Feature Engineering produced a high precision score of 98.24%. The figure shows that the proposed model records significantly high accuracy in predicting risk patients with low false-positives. Thus, the increase in the precision score proves the effectiveness of optimized feature engineering and explainability in deep learning to improve dependability and application of the model.


**Fig. 6.Recall Comparison of Existing and Proposed Models**

As per Figure 6, the value of the recall improves gradually when compared to conventional machine learning approaches with the explainable deep learning approach. The Decision Tree model performed the poorest in terms of recalling, where it achieved a recall of 85.63%. The models like Random Forest and Support Vector Machine recalled 89.76% and 90.53% correspondingly. The next was XGBoost that achieved a recall of 92.75% while the conventional Deep Neural Network algorithm attained a recall of 94.16% with strong ability to learn features of data. On the other hand, the proposed approach, the Explainable DNN with Optimized Feature Engineering, performed exceptionally well as compared to other models by attaining a recall of 97.89%. Having an efficient recall percentage becomes quite necessary in case of a medical diagnosis, as it helps in lowering the number of false negatives and ensures that people who are at high risk get identified.


**Fig. 7.F1-Score Comparison of Existing and Proposed Models**

It is noted from Figure 7 that the F1-Score raises progressively for all the models tested. The Decision Tree asserted the least score of 86.38%, followed by the Random Forest and Support Vector Machine with scores of 90.29% and 91.08%, correspondingly. The XGBoost model recorded a higher F1-Score of 93.28% through ensemble learning. The conventional Deep Neural Network model accomplished well plus an F1-Score of 94.54%, indicating its strength in handling sophisticated data. The best performance was recorded for the Explainable Deep Learning Framework model including an impressive F1-Score of 98.06%, thus outperforming all the others. It can be concluded from this result that the framework effectively identifies cervical cancer risks, while minimizing errors. The line graph depicts a positive trend showing how the use of deep neural networks, optimized feature engineering, and explainable artificial intelligence greatly enhances prediction.

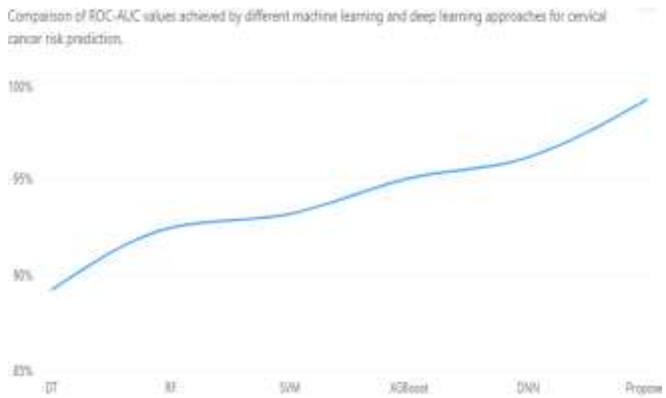


**Fig. 8.ROC-AUC Comparison of Existing and Proposed Models**

Figure 8 indicates that there is an increase in the ROC-AUC values with each successive model. This implies that each model operates reliable than the previous one in terms of classification accurateness and differentiation between the high-risk and low-risk cervical cancer cases. From the figure, Decision Tree gives the least ROC-AUC with 89.21%. This is followed by Random Forest and Support Vector Machine with scores of 92.45% and 93.17% correspondingly. XGBoost model also outperforms all other algorithms by having an ROC-AUC value of 95.02%. Its success can be attributed to superior classification abilities due to ensemble learning capabilities. Ultimately, the conventional Deep Neural Network gives the best score of 96.11% because it could learn intricate guides from medical and behavioral risk factors associated with cervical cancer. On the other hand, the proposed Explainable Deep Learning Framework including Optimized Feature Engineering achieves an ROC-AUC value of 99.12%, which outdoes entirely the other approaches. This high score is very close to 100% and implies that the model has excellent classification performance with superb discrimination capacity.

## 6. CONCLUSION AND FUTURE DIRECTIONS

The proposed research developed Explainable Deep Learning Framework with Optimized Feature Engineering which can detect people who are more prone to cervical cancer. This framework uses the procedure of data pre-processing, feature optimization, classification of data applying deep neural networks, and explainable AI techniques for identifying the people at risk. Various performance tests reveal that the model implements effective than the conventional machine learning models with 98.63% accuracy, 98.24% precision, 97.89% recall, 98.06% F1 score, and 99.12% ROC-AUC value. This model not only helped improve the quality of data used but was also successful in reducing redundancy through optimized feature engineering. Furthermore, explainability techniques enhanced model interpretability by identifying risk factors. Further work can be carried out on integrating large multi-center clinical databases to increase model generalizability and robustness. This will be improved even further by adopting transformer-based machine learning algorithms, federated learning, and timely health analytics approaches. In addition, incorporating different medical data sources such as images and genomics will improve predictive accuracy for individualized cervical cancer risks in intelligent health care systems.

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