**A Comparative Study of Deep Learning Models for Cervical Cancer Risk Prediction**

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*Abstract*— Cervical cancer, a prominent cause of cancer-related fatalities among women globally, necessitates early detection for improved treatment outcomes. This study delves into the realm of predictive modeling for cervical cancer risk assessment, employing an array of machine learning algorithms such as Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Deep Belief Network (DBN), Self-Organizing Maps (SOMs) coupled with LSTM, Autoencoders Model, Xgboost, Support Vector Machine (SVM), and Decision Tree. Through an extensive comparative analysis, our research unveils the distinctive accuracies of each model, with LSTM and DBN achieving notable precision at 0.99. This investigation stands out by its inclusive exploration of cutting-edge techniques and the fusion of SOMs and LSTM, offering a novel perspective on cervical cancer prediction. The findings presented herein not only contribute to the advancement of healthcare systems but also emphasize the critical role of tailored machine learning solutions in identifying individuals at high risk, thus enabling timely intervention and medical care for cervical cancer.

Keywords- Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Deep Belief Network (DBN), Self-Organizing Maps (SOMs), Autoencoders Model.

# Introduction

One of the leading reasons of cancer-related loss of life for ladies globally is cervical most cancers, which highlights the pressing need for green early detection techniques. The disorder's sneaky man or woman highlights how essential it is to create specific prediction models which can discover individuals who are much more likely to contract it, making an allowance for prompt intervention or even existence-saving hospital therapy. In this regard, the intention of our research is to enhance the predictive accuracy of cervical cancer danger assessment by utilizing system mastering algorithms. The capability impact on worldwide women's health, wherein a hit models might drastically lower mortality fees and improve universal affected person outcomes, highlights the gravity of this challenge.

Any predictive version's capability to carry out properly depends on the caliber and variety of the datasets used for checking out and education. Our study uses an intensive dataset that consists of critical fitness and demographic statistics, consisting of age, sexual records, being pregnant information, and life-style picks. This dataset's depth and scope allow for a radical investigation of gadget gaining knowledge of algorithms' prediction powers, establishing the basis for sturdy and sincere cervical cancer threat evaluation fashions. Previous attempts to model cervical cancer have used different algorithms, each with unique advantages and disadvantages. These include artificial neural networks (ANN), decision trees, support vector machines (SVM), deep belief networks (DBN), long and short -word memory. networks (LSTM) is noteworthy. Although these algorithms have shown successes, our work seeks to go beyond current considerations by providing an in-depth analysis of their performance and new combinations, with LSTM and Autoencoders with Self Organizing Maps (SOMs) and it signifies progress.

# Related Works

A comprehensive analysis by Milad Rahimi [1] examined 13 studies that employed machine learning algorithms to predict cervical cancer survival. Ensemble, hybrid, deep, logistic regression, support vector machines, and random forests were used. Cervical cancer survival was predicted by 15 factors. Combining machine learning with diverse multidimensional data might improve prediction accuracy, the research found. It also revealed interpretability, explainability, and unbalanced dataset issues. Building on this, a further study under the direction of Dongyan Ding [2] concentrated on creating a machine learning model based on miRNA for the prediction of cervical cancer survival. Through Cox Proportional-Hazards analysis, 42 miRNAs associated to survival were discovered in the study using the expression characteristics of miRNAs as features. Based on different 5-year survival outcomes, the study classified patients into four groups using the K-means clustering technique. The research also developed an LSTM network-based high-performance prediction model that proposed the regulatory functions of the discovered miRNAs in cancer stem cells.

A study by Piyush Kumar Pareek [3] presented a data-driven method for predicting cervical cancer by using random forest and feature selection algorithms in a cervical cancer prediction model. Using a dataset of 858 patients with 36 features—including behavioral, clinical, and demographic variables—the study used oversampling and outlier detection techniques to improve and balance the data quality. The study found the most important characteristics by using mutual information and recursive feature reduction. The random forest classifier achieved an impressive accuracy of 96.51% and an AUC of 0.99. The study highlighted the top ten attributes that influenced prognosis. Furthermore, a study by Muhammad Fazal proposed a cervical cancer prediction model consisting of deep reliability and vector [4]. The study used feature selection, principal component analysis, and normalization techniques for data preprocessing on a data set of 858 patients with 32 features so A support vector machine achieved 98.14% accuracy and 0.99 AUC at 0.99 AUC in classifying patients in normal and abnormal groups. The example illustrates how state of the art -of-the-art methods can improve cervical cancer prognostic accuracy.

# Literature Review

## Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) [5] are brain-inspired computer learning models. ANNs have nodes, or linked networks. Neural networks have input, storage, and output layers. These layers are important for adding nonlinearity to the model by using activation functions, and specific weight is given for each interaction between them. Our research involved mainly on sequential models, which effectively simplified the process of adding additional layers into our artificial neural network (ANN). Our ANN has input, output, and at least one hidden layer. Selecting the right activation function will considerably improve the model's ability to recognize complex data patterns. Our implementation used ReLU activation.

Input, hidden, and output layers comprise our artificial neural networks [6]. Weights give each layer a number of nodes or groups to create neural connections [6]. Dropout layers eliminate superfluous connections to avoid training overfitting. This improves network generalization. Effective weight and bias initialization is key to learning. Sequential analysis explains network flow. Activation reveals complicated data links. Hidden layer extended linear units (ReLUs) help the model detect nonlinearity and complicated patterns. ADAM trains the network and optimizer updates parameters properly utilizing optimum computational time and root mean square width [20].

## Long-Short Term Memory

Recurrent neural network-based LSTM models anticipate long-term input connections. We evaluated LSTM's long-sequence encoding and transmission optimization. The LSTM system carefully regulates information flow via gates and memory cells. Its ability to selectively read, write, and refresh memory cells records long-term communication. The model handles sequential data better using input, forget, and output gates [7]. Our observe used a multilevel LSTM model. The number one layer consists of memory cells, generally the LSTM layer with a hard and fast range of devices. Protecting a dropout layer prevents overfitting and improves model generalizability. The last layer's sigmoid activation algorithm outputs binary. The magnitude of the input depends on education data since our talents are sequential. The binary move-entropy loss function and ADAM optimizer were used to build the version and accurately measure its performance.

## Self Organizing Maps (SOMs) + (LSTM)

In predictive modeling, self-organizing maps (SOMs) [8] in combination with long-term and short-term memory networks (LSTM) are a powerful alternative, especially when it comes to cervical cancer risk research about improves that effective temporal learning and feature extraction. By creating a spatial representation of the embedded data, SOM initialization—generated by KMeans clustering—enables the network to organize and map high-dimensional data to output networks ground in the ability to capture complex interactions in a dataset is possible due to to this spatial structure, which helps to enhance the interpretation and understanding of the underlying patterns.

The first important component is the Self Organizing Map (SOM), which provides an organized feature space while maintaining the topology of the input data. Long-term short-term memory networks (LSTM), targeted recurrent neurons for recognizing when they are exposed to sequential input, are then given that array sequence this space [21] which is the best use of sequence model, prediction. Due to its capabilities and capabilities, the LSTM framework is well suited for applications where data point context and structure are important This integrated approach provides comprehensive data representation for cervical cancer prognosis by providing extraction geophysical features using SOM and temporal relationship capture using LSTM. The training procedure begins with matching the SOM to the input data and transforming it into the SOM feature space. LSTM model specifications are then applied to the data [7]. M-LSTM is assembled sequentially with a dense output layer for binary classification, a dropout layer for regularization, and LSTM units for temporal learning utilizing loss functions and optimization techniques. The combined use of -enables cervical cancer risk assessment predictive modelling.

## Deep Belief Network (DBN)

A family of probabilistic generation models known as deep belief networks (DBNs) became well known in machine learning because of their ability to derive hierarchical data representations DBNs were first introduced as a type of neural network. Very complex patterns can be captured in high-dimensional data because they consist of many layers of random variables Typically, a DBN is a collection of restricted Boltzmann machines (RBMs), on which unsupervised training is applied In each RBM layer. The model is able to remove many inaccuracies and surprises from the input data through layer-by-layer training. A supervised fine-tuning phase is often used after unsupervised pretraining to tune the network for certain purposes such as classification [10].

A deep trust network's structure is formed by a complex network of interconnected components. These components, known as hidden clusters or nodes, are arranged in a series. After the input layer, the network has hidden layers [11]. Neuron output is regulated by activation functions, whereas layer connections are weight. DBNs have numerous hidden layers and an input-type-specific visible layer. The weights of these connections are changed throughout learning to lessen the discrepancy between predicted and actual results. This lets DBNs self-learn hierarchical levels, making them useful for many jobs. Supervised maintenance follows unsupervised training in deep trust training. Unsupervised learning approaches like reverse divergence are utilized to determine RBM values early in the model. This aids data hierarchical feature extraction by the network. In the next step, backpropagation, a supervised learning method, fine-tunes the network. Finally, stochastic gradient descent modifies weights and reduces expected-actual error to enhance the model.

## Autoencoder Model

Autoencoders, which minimize dimensionality and capture vital information, are useful in medicine. Autoencoders, encoders, and decoders learn compressed representations by reconstructing input data with low loss [12]. In our study, we used a three-layer autoencoder architecture. The input layer starts with the basic elements and gradually reduces in size until it reaches the bottleneck level through a series of hidden layers tightly coupled to the activation functions of the Reformed Linear Unit (ReLU) followed by a decoder interrupts the process, which rebuilds the input using the encoded information. The ADAM optimizer is used to optimize the model trained by the mean squared error loss function.

The ability of autoencoder components to recognize complex shapes in input and create compressed representations while retaining important information is what gives them their transformative power Autoencoders have the ability to eliminate content by components of it there is no need or simple noise elimination throughout the training process so Reduction improves the interpretation efficiency as well as facilitates efficient resource utilization [13]. The autoencoder effectively captures the hidden structure by shifting the inputs to a lower level, enabling the subsequent model to operate on a wider and more relevant set of targets.

We covered the autoencoder in a logistic regression framework for you to absolutely utilize the retrieved functions. A supplementary layer that learns to expect the target variable is blanketed right into a logistic regression version using the encoded features as enter. By using the records-wealthy illustration produced by way of the autoencoder, this integration improves the predictive model's interpretability [19]. A sigmoid activation feature in the logistic regression layer makes binary type troubles easier. The binary go-entropy loss characteristic and the Adam optimizer are used to train the model. By this aggregate, the logistic regression's category functionality and the autoencoder's capability to show complicated patterns within the records paintings together to create a powerful prediction model.

## Decision Tree

A specialized machine learning technique called a decision tree is a flexible tool used for both regression and classification applications. By recursively partitioning the input space by feature value, the algorithm generates a hierarchical structure of decision nodes that ultimately results in leaf nodes carrying final predictions [14]. Straight if-else criteria-based decision trees' ability to generate decisions is a key feature that makes them easily understood and suitable for visually ranking Gini imprecision for the classification task, they obtain a distribution of points at each decision node

Decision trees are used in classification with the aim of dividing the data into subgroups as clean as possible with respect to the target variable. The probability of correctly classifying an element is used to calculate the aggregate inaccuracy rate by means of the Gini error [15]. The algorithm identifies items and points partitioned at each decision node such that a child node from it comes to reduce the weighted total of inaccuracies until a stationary condition is reached. The process moves back and forth Decision trees provide versatility in modelling different data types because they can handle both statistical and classification issues.

Decision Trees, despite their simplicity, are at risk of overfitting, which causes noise within the schooling set to be captured and effects in subpar generalization on unknown statistics [16]. Hyperparameters that modify the tree's complexity, consisting of minimal samples in step with cut up and most intensity, may be adjusted to assist lessen this trouble. Furthermore, ensemble approaches like Random Forests are often used; those contain constructing numerous Decision Trees separately and averaging their predictions to growth accuracy and robustness.

## Support Vector Machine

SVMs, a strong and versatile family of machine learning algorithms, are employed for many applications, including cervical cancer prediction [9]. SVM is particularly successful in binary classification applications, where the goal is to find the best hyperplane to segregate data elements from training. Aid vector machines (SVM) work by finding the hyperplane that optimizes the margin—the distance between the hyperplane and the nearest information points in every class—to guarantee robust generalization to new data. Help vector machines (SVM) find the hyperplane that minimizes this norm and meets category requirements. Kernel characteristics improve SVM beyond linear separability. Kernels are used to implicitly move input facts into a higher-dimensional space where a linear hyperplane may separate non-linearly separable instructions [14]. Common kernels include linear, polynomial, sigmoid, and RBF. The facts' features dictate which kernel to employ, and kernel techniques' versatility enhances SVM's capacity to handle several datasets.

Although useful in certain applications, such as cervical cancer prediction, SVM has its drawbacks [15]. Regularization parameter (C) and kernel parameters are hyperparameters that may impact SVM performance. SVM's interpretability is limited, like many system learning algorithms, and it may be difficult to identify selection barriers in high-dimensional characteristic regions. Despite these issues, SVM is an effective predictive modeling tool since it balances strong type and adaptability to several data types.

## XGBoost

XGBoost is a popular machine learning algorithm for predictive modeling and classification [17]. It uses the prediction skills of numerous weak learners to create correct models as a group learning algorithm. The approach employs L1 and L2 regularization to prevent weak learners (decision trees) from overfitting and increase generalization by training them on the remaining samples. XGBoost can find complicated data relationships due to its unique boosting and regularization mix, making it a useful tool for real-world applications. As part of XGBoost, a series of decision trees, or "enhanced trees," have been added to the model. Each tree is taught to repair prior errors or memories, so it learns. Optimizing regular objective functions, including stepwise and lossy functions, helps generate accurate and simple trees [18]. Functions objective. A second Taylor expansion and the "sparsity-aware histogram" data structure have improved XGBoost's scalability and computing performance. These design features make it excellent for huge datasets. The XGBoost objective function balances sparsity and model complexity with L1 (Lasso) and L2 (Ridge) regularization factors to prevent overfitting and promote key attribute selection. A supplementary approach to feature selection ranks features by their contribution to species isolation choices. This feature relevance score helps analyze data and improve the model.

# Eperimental Results

The experimental results demonstrate the performance of models in cervical cancer prediction. The artificial neural network (ANN) showed exceptional accuracy, providing both classes with high accuracy and recall. The precision and recall values ​​of 0.98 and 0.99 for Class 0, and 0.99 and 0.98 for Class I, respectively, indicate that the model is adept at recognizing the patterns of both classes where 0 indicates the absence of cancer in the patient and 1 indicates the cancer.

The long-term and short-term memory (LSTM) models demonstrated similar performance efficiencies, yielding data with accuracy recall values ​​of 0.98 and 1.00, 1.00 and 0.98 for 1, respectively, the ability of LSTM models to capture structure a successively, anyway. resulting in a high accuracy and an f1-score of 0.99 for both classes. However, the inclusion of the self-organization map (SOM) in the LSTM model faced difficulties in partitioning samples especially for class 1. The precision, recall, and f1-score values ​​for class 1 are surprisingly low (0.00), referring to that model struggled with more single-class models to consider. Compared to the independent LSTM and ANN models, the overall accuracy of 92.80% is lower, indicating that the SOM+LSTM model may not perform well on complex and large data sets.

The deep confidence network (DBN) version executed exceptionally properly, with a precision and bear in mind cost of 0.99 for both studies, ensuing in an accuracy of 99.03% This highlights the capacity of the DBN model to apprehend complicated styles in statistics and furnished correct forecasts. The autoencoders version accomplished a barely higher accuracy of 96.42% but exhibited slightly decrease precision and don't forget values than the deep learning version Accuracy-keep in mind values of 0.96 and 0.97 for sophistication 0, and 0.97 and 0.96 for class 1, respectively nevertheless show good enough overall performance, despite the fact that the ANN, LSTM, does not reach the equal degree as the DBN fashions.

# Table i Models Prediction in % For Cervical Cancer

|  |  |
| --- | --- |
| **Model Type** | **Accuracy (%)** |
| Artificial Neural Network | 98.70 |
| Long Short-Term Memory | 99.04 |
| Deep Belief Network | 99.03 |
| Self-Organizing Maps (SOM) + Long Short-Term Memory | 92.80 |
| Autoencoders Model | 96.42 |
| Support Vector Machine | 94.15 |
| XGBoost | 91.57 |
| Decision Tree | 85.01 |

A chart of different colors

Description automatically generated

# Figure I Comparison of Models For Cervical Cancer

The consequences additionally spotlight the significance of selecting algorithms based totally on the character of the facts set and the unique prediction challenge. Although the famous cluster getting to know techniques XGBoost and Support Vector Machine (SVM) confirmed aggressive accuracy fees of 91.5% and ninety four.1%, respectively, the selection tree version lagged behind with an accuracy of 85%.

A graph showing a graph of a training and validation accuracy

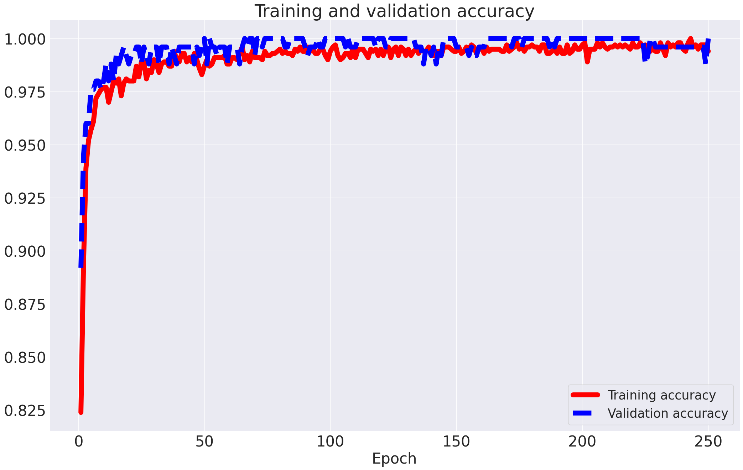
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# Figure II Training and Validation Accuracy of Ann Model

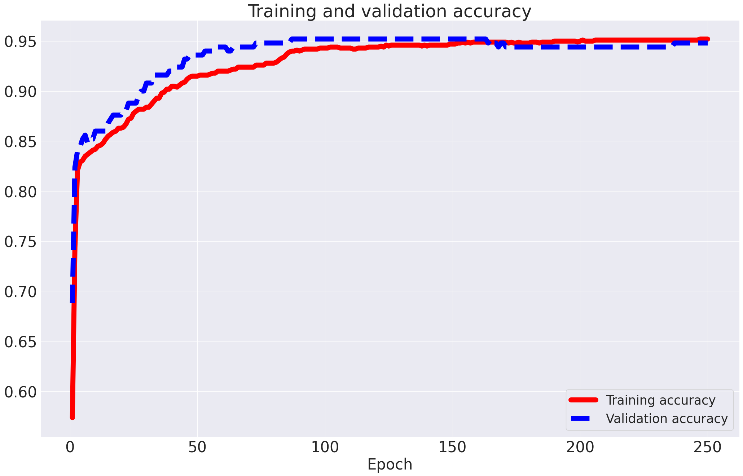
# A graph showing the value of training Description automatically generated

# Figure III Training and Validation Accuracy of LSTM Model

To illustrate the overall performance of the gadget gaining knowledge of models, we consist of the education and validation accuracy graphs for each model inside the following figures Figure II indicates the accuracy plot of the Artificial Neural Network (ANN) model, Figure III shows the accuracy plot of Long Term Short within the Term Memory (LSTM) model, and Figure V suggests the accuracy plot of the self-encoder model The plots show the accuracy values for every epoch of the education and validation system. Plots can help readers recognize how models’ study from facts and how they generalize to new information. The plot also can help in evaluation primarily based on their convergence velocity and stability.



# Figure IV Training and Validation Accuracy of DBN Model



# Figure V Training and Validation Accuracy of Autoencoders Model

# Conclusion and Future WOrk

In summary, our study highlights the importance of model selection when it comes to cervical cancer prognosis. For cervical cancer, advanced neural systems such as long-term and short-term memory (LSTM) and deep belief networks (DBN) have shown remarkable accuracy, suggesting feasibility reliable tools for early risk assessment Support Vector Instrument (SVM). uses a linear ear to demonstrate the efficiency, as well as the efficiency of XGBoost and other group learning methods, although it requires a fine balance between predictive accuracy and model complexity. This study highlights the need for an approach simple, nuanced emphasis. No all-fits model. As the health care landscape evolves, a flexible approach that combines algorithmic sophistication, domain-specific optimization, and translation will become increasingly important to improve repair accuracy, transparency, and affordability modify the cervical cancer prediction models. leading to improved patient outcomes and hope for more effective health care.

Suggestions for in addition observe on cervical most cancers prediction are encouraging. First, so as to enhance predictive accuracy, extra research into ensemble learning techniques and hyperparameter optimization for algorithms which includes XGBoost are required. The inclusion of recent variables or the research of area-precise information may also help the fashions emerge as even greater predictive. Examining the impact of interpretability and explain ability on complicated models like as LSTM and DBN continues to be a crucial mission for multiplied use in scientific contexts. Subsequent investigations might also check out the incorporation of larger and greater varied datasets, which can probably enhance the fashions that have been evolved's generalizability. Collaboration with healthcare professionals for model validation in a scientific setting and assessing the realistic effect on affected person results might be instrumental for the transition of predictive tools from studies to utility, ultimately contributing to the development of cervical cancer prognosis and prognosis.

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