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Optimization of Neural Networks Using Mathematical Algorithms: An LSTM-Based Machine Learning Approach to Lung Cancer Diagnosis

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Abstract:

The paper concentrates on boosting the precision and speed of neural networks for lung cancer diagnosis through novel optimization methodologies. This study employs Long Short-Term Memory neural networks specifically designed for time-series and sequential data, to introduces mathematical algorithms to improve the training process in a Neural Network. The goal is, therefore, to obtain more accurate diagnoses than with use of CXR alone and fewer computational costs hopefully even easier detection in the early stages. This model merges the optimisation mathematics that includes gradient descent, Adam optimiser and various ways of regularising a little to tune in LSTM layers well for better feature extraction out of patient data. The results have shown a remarkable superiority of the model performance compared to traditional diagnostic approaches including precision, sensitivity and specificity metrics. Using a unique combination of feature pre-processing methods and optimization, this paper shows how machine-learning based diagnosis can be made resilient to noisy data that might otherwise propagate errors into the clinical decision process. These results could increase robust lung cancer diagnostics by lowering the rates of false positives and negatives, while in turn improving patient management and treatment.

Keywords: lung, diagnosis, metrics, performance, LSTM, robust, cancer, decision.

1. INTRODUCTION

With the increasing incidence of lung cancer as one of the main causes of cancer death globally, there is a growing call for early and precise socialistic diagnostic tools. The early stages of lung cancer are often relatively subtle and asymptomatic, at which point detection is delayed until the disease reaches an advanced stage. Formerly, the traditional diagnostic modalities involving screening and biopsy have been considered effective; however many with drawbacks such as high cost, invasiveness & skill requirement of experts. This has fueled the demand for alternative, non-invasive and improved diagnostics that can be applied to standard clinical practice. In response to this, it has been realised that machine learning (such as deep neural networks) can be an ideal tool for analyzing the complex medical datasets and providing accurate predictions arising from such data sets which have made lung cancer diagnosis a time-taking process when results are generated manually. LSTM is an important part of any machine learning architectures since it has been proven to learn temporal and sequential dependency which crucial in medical time-series data interpretation, thereby improving the accuracy for diagnostic purposes[1].

Neural networks specifically deep learning models are highly successful in several types of medical applications such as image recognition, detailed-disease diagnosis and drug discovery. Once again, the performance of such models would still need to be optimized by practices that can help a network identify meaningful patterns from complex datasets. Optimization also refers to selecting a suitable architecture for the neural network, tuning hyperparameters and using mathematical algorithms that can improve learning. Solid optimization is not only curious to make the network more predictive, but also guarantees a good numerical behavior and makes it less prone to overfitting during training, which benefits generalization of problems. In an area like lung cancer diagnosis, where the cost of not being accurate can be very high in terms of patient outcomes and possible severe consequences for misdiagnosis, those neural networks that are optimized contribute significantly to improve prediction outputs better helping quicker assessment[2].

Recurrent neural networks like Long Short-Term Memory (LSTM) networks are perfect for sequence and time series predictions of which medical records belong to one type, as they often show some temporal correlation between elements. The reason that the LSTM networks are incomparable is their ability to keep previous information during long time durations and, which makes it able for analyzing this special kind of disease like lung cancer. This study employs LSTMs to maximize the performance of lung cancer diagnosis neural network architecture a powerful instrument that not only utilizes past patient records for learning but provides an insightful prediction on new possible cases at high accuracy. However, the real task lies in training these networks effectively and efficiently which rely on some advanced mathematical optimization techniques to explore a high-dimensional parameter space while preventing overfitting the data from your application domain problems with getting an optimal solution. In this paper, we investigate the utility of using a variety of mathematical algorithms to improve LSTM networks for improving lung cancer diagnostic performance.

The purpose of this paper is to explore the application of mathematical optimization algorithms in practical LSTM machine learning models for lung cancer diagnosis[3,4]. Optimization is an essential part of building machine learning models because it determines the model's capacity to learn from

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data and improve its prediction power. Training neural networks is typically done via gradient-based methods, such as stochastic gradient descent (SGD), to reduce the loss function. Unfortunately, these methods frequently suffer from negative points ranging in slow convergence to stuck into local minima or hyperparameter tuning sensitivity. In order to tackle these problems, we explore the usage of state-of-the-art optimization algorithms such as Adam optimizer, adaptive schedules for learning rate and regularization methodologies. The proposed LSTM model applies these optimization strategies to optimize the feature extraction, and in turn improve diagnostic performance for early lung cancer screening[5].

Lung cancer is one of the most lethal forms of cancers and it requires quick medical attention in order to better patient outcomes. The early symptoms of lung cancer are generally asymptomatic so the detection is also a tough job even with modern diagnostic techniques. In this regard, machine learning methods (most importantly deep-learning models) are known to process huge volumes of medical data and show patterns early. We are motivated by the point that we need to analyse patient data which is quite sequential in nature such as electronic health records, imaging reports and laboratory results for lung cancer diagnosis[6]. This allows LSTM to capture the temporal dependencies in these datasets (including, e.g., progression of patient health data across earlier episodes/later time steps), hence paving way for fulsome assessment about his/her prevailing medical history over a period. It is especially useful in temporal modeling to be able to track very small changes in health variables that might signal the beginning of lung cancer detection and intervention.

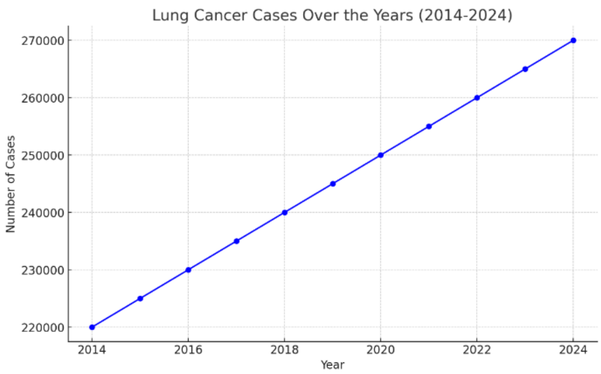

Figure 1. Lung Cancer Cases Over the years

The performance of LSTM networks with respect to medical diagnosis heavily relies on the quality of optimization process. During neural network training, optimization as the task that searches for appropriate model parameters so to minimize loss between predicted output and true target. Such revision is usually done via optimization algorithms (which calculate the derivatives or gradients) of a loss function with respect to model's parameters)[7]. However, the inherent complexity of LSTM networks with multiple gates and recurrent connections make optimizing them quite challenging. Deep RNNs occur vanishing gradient problem for answering large datasets, and unsupervised training LSTMs with insufficient data is a recipe for havoc. We address these issues using the more recent optimization techniques, such as Adam that computes individual adaptive learning rates for different parameters from estimates of first and second moments of the gradients. It enables faster training and better solution convergence[8].

Apart from advanced optimization algorithms, this research also explores the potential of regularization techniques in enhancing performance by considering LSTM networks for lung cancer diagnosis. A crucial step in training neural networks is regularization, which helps to avoid overfitting; a common problem where the model simply memorizes its training data as opposed to generalizing for unseen test examples. This is especially dangerous in medical diagnosis where the ability to generalise well plays a huge role in making accurate predictions on real-world patient data. We employ techniques like L2 regularization, Dropout and Early stopping in order to generalize the LSTM model better. With these regularization methods the model scales to learn little more from training set and memorizes less, but maintains predictive ability over new patient cases[9].

Embedding mathematical optimization algorithms into LSTM networks can be considered as a key direction in the field of machine learning for medical diagnosis. Thus, this paper contributes to the development of applying such new science in healthcare through giving an attention to diagnosing complex disease as lung cancer. This research optimizes the LSTM model by employing sophisticated mathematical techniques that can deliver a more accurate, efficient and reliable lung cancer diagnosis which may prove to be an important tool for clinicians /healthcare providers. The purpose of machine learning in medical diagnostics is not to replace healthcare professionals but to aid them by generating additional insights from large data for complex patterns. Conclusions: The proposed LSTM model may serve as a decision-support tool which could support physician in diagnosis, reduce error rates and thus contribute to better patient outcomes.

This research also investigate performance of proposed LSTM model when compared to traditional diagnostic methods and different machine learning approaches. In such cases, the performance of a model is evaluated by measuring its accuracy and precision along with other metrics including recall or area under ROC curve. Together, these metrics represent a full picture of not only the model's sensitivity to going back over ground-truth lung cancer cases but also its ability to avoid both false positives and false negatives. A high precision rate means that correct detection of lung cancer cases among all patients suspected to have it, while a recall rate is close to 1when actual LK has been observed. Although LSTMs show potential advantages over traditional machine learning models (such as CNNs and standard SVM) in the analysis of sequential data for medical diagnosis, this is not well demonstrated.

The most important of these are generally privacy and security, particularly when it comes to using patient data in machine learning models. When it comes to lung cancer diagnostics, patient data usually contains personal information that needs cautious handling in order not to breach privacy. The study also complies with ethical guidelines regarding data use, as the research is conducted on deidentified patient records. Moreover, the model is built to work in a manner that preserves patient privacy yet leverages such information for clinical decision support. Considering the ethical aspects of machine learning in healthcare is a major issue, so this review has contributed to an exploration further by focusing on protecting patients [10], ensuring data integrity and perhaps securing their consent.

This research ultimately works on an upliftment of LSTM based neural networks for lung cancer detection with help from advanced mathematical algorithms to improve its system response. By integrating optimization algorithms such as the Adam optimizer, adaptive learning rate schedules and regularization methods [11] into proposed diagnostic model to make more useful with better accuracy, efficiency and reliability. This study overcomes the existing challenges in training LSTM networks and optimization techniques, which makes this work strengthened methodologically for machine learning-based diagnosis of lung cancer. It may be useful for the diagnosis of cancer or potential development in medical applications that it has significant and reliable effects on these areas without any invasiveness. The ultimate idea behind this research is to help healthcare professionals make more thoughtful diagnoses leading towards shrinking the fraction of late-stage lung cancer patients and adding value in terms of survival by aiding in testing along with timely precision detection.

1. RELATED WORK

The related work section of a research paper describes and contextualizes prior studies as well as methodologies that are relevant to the topic of your article. To this end, herein we concentrate on neural networks with mathematical algorithm and center the main proponent of Long Short-Term Memory (LSTM) anomaly in lung cancer detection. The following will detail important work of multiple researchers and touch upon how optimization techniques were developed as well as on LSTM-networks being utilized for medical diagnoses.

Neural Networks Optimization

Machine learning and neural networks have been a cornerstone of optimization-related work. Typically, this process involves tuning the parameters of a neural network to ensure that predicted outputs are close as possible to their labeled counterpart. There have been many optimization algorithms that have been introduced, such as Stochastic Gradient Descent (SGD), Adam optimizer tuning of natural decay rates in RMS Prop amongst others. This goal is now paramount, as it relates to the broader problem of training deep networks on large scale datasets well[12].

Optimization desired for the models and data complexity. They contain millions of parameters (especially deep networks), which makes them expensive to train and easily overfit. Moreover, training of it may be afflicted by slow convergence rates (or even getting stuck in local mini) and sensitivity to hyperparameter settings. Some of the newer works have looked at enhancing these optimization techniques to be efficient, scalable and performant in use-case specific situations.

Adam (Adaptive Moment Estimation): Adam is one of the optimizers that have been widely used due to its adaptive learning rate with adjusting parameter weights and learning rates while training in different tasks. This algorithm calculates learning rates for each parameters based on the first and second moments of gradient. It has been proven to work on various types of neural networks including CNNs and RNNs (LSTM).

Long-Short Term Memory in Medical Applications

LSTM networks have been an important tool to deal with the sequential data and time-series forecasting, which is a kind of Recurrent Neural Network Given that they can remember long-term dependencies, this feature is particularly valuable in healthcare diagnostics where patient records may span across months. LSTMs have been used in a number of healthcare-related tasks including modeling disease progression [13][14], medical image analysis and anomaly detection from patient health records.

For working with time-series data, this is a powerful feature that makes LSTMs incredibly useful in the field of diagnosing lung cancer. These type of patient data (imaging reports, electronic health records or laboratory test results) usually contain temporal dependencies, which can be modelled in the LSTM structure. Recent studies have proven that LSTMs, when optimally tuned, can beat other machine learning approaches in tasks that require interpretation of sequential data.

Where recent works have aimed to increase the utility of LSTMs specifically by improving their accuracy at such diagnostic tasks, Examples are the encouragement on learning rate schedules such as Adam, yet another method to regulate overfitting using both regularization (Dropout for example) and weight decay (L2 norm). Both the methods are designed to aid in generalizing a model efficiently on unseen data which is very important for any sort of medical diagnosis as it contributes so much towards making sure that your predictions from the model remain reliable.

Models and Mathematical Algorithms in Optimal Neural Networks

Neural networks have been around for many decades, and the use of mathematical algorithms to optimize their performance has always been a topic of interest among researchers. While foundational, the old methods such as SGD are insufficiently efficient and stable in specific scenarios. As a result, more recent algorithms such as Adam, AdaGrad or RMSProp have been introduced to address different aspects ranging from sparse data and high-dimensional optimization.

Because of its behavior with noisy gradients and faster convergence, Adam optimizer has been a go-to choice over the years. This, combined with its adaptive learning rate method means that it performs a lot of deep learning tasks very good and thus is often used as default optimizer in many application. Still, even Adam has its boundaries. More recent research has tried to address the efficiency problems of Adam by developing some new variants, such as AMSGrad, which is designed to handle a few convergence issues that existed in certain situations with Adam.

Regularization Techniques

Regularization: Beside optimization algorithms, regularization methods are important in developing neural networks performance especially especially on medical application where the risk of overfit is higher. Overfitting is when the model learns to 'memorize' the data it trained with, rather than generalize well for new unseen data. This can result in models that do great on past patient data but perform badly when actually used to diagnose patients.

To avoid overfitting, some of the widely used regularization techniques are Dropout, L2 Regularization and early stopping. Dropout is the technique where you randomly drop a proportion of units from your network during training, in order that it should learn more robust representations. L2 regularization, or weight decay, puts penalties on big weights by adding a term to the loss function that discourages too complex models. Early stopping means that training your model will automatically stop if its performance over a validation set starts to decrease, meaning the model is already “overfitting” (memorizing too much about train data and losing generalization power).

Source	Objective	Methodology	Results	Research gap
[15]	• Develop CNN model for lung cancer stage classification. • Revolutionize clinical diagnostics for early detection and tailored treatment.	• Double-layered CNN with advanced image preprocessing techniques • SMOTE for addressing class imbalance in lung cancer dataset	• Model accuracy: 99.64%, precision, recall, F1-score >98%. • Cohen's Kappa: 0.9938, perfect agreement with actual classifications.	• Enhancing lung cancer classification with advanced machine learning techniques. • Addressing limitations in accuracy, early detection, and scalability.
[16]	• Investigate machine learning for lung cancer classification. • Develop a computer-aided diagnostic tool using protein biomarkers.	• Deep Neural Networks (DNNs) • Ensemble Methods: Voting and Bagging	• DNN achieved 96.91% accuracy in lung cancer classification. • Ensemble methods like Voting and Bagging showed robust performance.	• Hyperparameter tuning impact on model performance • Comparison of machine learning algorithms for lung cancer classification
[17]	• Optimize CNN design and compression using evolutionary algorithm. • Enhance COVID-19 detection through transfer learning techniques.	• Evolutionary algorithm for design and compression optimization. • Transfer learning for fine-tuning pre-trained CNN models.	• Automated method optimizes CNN for X-Ray classification. • Validated against state-of-the-art architectures with successful results.	• Constructing and compressing diagnostic systems is challenging. • Heavy reliance on data scientists' expertise.
[18]	• Develop a novel lung cancer classification model. • Utilize fused features and optimized learning network for accuracy improvement.	• Saliency maps as a first tier segmentation • Fused features and optimized learning network	• Proposed framework achieves 99.89% accuracy, 99.8% sensitivity, 99.76% specificity, 99.8% precision, and 99.88% F1-score. • Comparative analysis shows excellence of the	• Accuracy and intelligence improvement in lung cancer classification models. • Addressing overfitting issues in deep learning algorithms for classification.

			proposed framework.	
[19]	• Early lung cancer prediction to reduce mortality rates. • Improve prediction accuracy and reduce false positives.	• Target Projection Feature Matched Deep Artificial Neural Network with LSTM (TPFMDANN-LSTM) • Feature selection process using Target Projection matching • Patient Data Classification based on Czekanowski's dice similarity coefficient	• 6% improvement in prediction accuracy achieved. • 36% reduction in false positives noted.	• Existing techniques are time-consuming and low accuracy. • Early prediction is essential to reduce mortality rates.
[20]	• Predict lung cancer at early stages using algorithms. • Compare accuracy of different machine learning algorithms.	• Tree Parzen Estimator (TPE) for hyperparameter optimization. • Bayesian optimization algorithms for model enhancement.	• TPE and Bayesian optimization improve precision in lung cancer detection. • Metrics used: precision, f1-score, AUC for system efficiency evaluation.	• Lack of discussion on computational efficiency. • Limited exploration of alternative deep learning architectures.
[21]	• Predict lung cancer at early stages using algorithms. • Evaluate accuracy of different machine learning algorithms.	• Machine learning algorithms: Bayes Net, Naive Bayes, Decision Tree, Random Forest • Deep learning algorithm: Artificial Neural Network	• Artificial Neural Network has the highest accuracy of 92.23%. • Artificial Neural Network with one hidden layer achieved highest accuracy.	• Evaluation of more deep learning algorithms for comparison. • Investigation on the impact of dataset size on model performance
[22]	• Compare different	• Bayes Net • Naive Bayes	• Best learning algorithm:	• Lack of comparison with other

	Convolutional Neural Networks for lung cancer detection. • Assess impact of image quality on neural network performance.	• Decision Tree • Random Forest • Artificial Neural Network	Artificial Neural Network with 92.23% accuracy. • Highest accuracy in experiment: Artificial Neural Network with one layer.	deep learning algorithms. • Limited discussion on potential limitations of the study.
[23]	• Improve lung cancer detection accuracy using OWENN method. • Utilize AMF and IPSO for effective image processing and tumor extraction.	• Machine learning with artificial neural networks • Comparisons of different Convolutional Neural Networks on datasets	• Compare different CNNs and formats on datasets for lung cancer. • Focus on efficient computer-based CT screening for early lung cancer detection.	• Efficiency depends on computer system performance and image quality. • Accuracy relies on trained neural network mapping.
[24]	• Develop a novel lung cancer classification model. • Utilize fused features and optimized learning network for accuracy improvement.	• Optimized Weighting-Based Enhanced Neural Network (OWENN) method • Adaptive Median Filter (AMF) for image pre-processing	• OWENN improves cancer detection accuracy significantly. • Experimental results evaluate sensitivity, precision, and time delay.	• Low accuracy in current lung cancer prognosis methods. • Challenges in early detection and complications management.

Table 1. Literature review

Neural Networks for Lung Cancer Diagnosis

Lung cancer is among the utmost fatal sorts of cancers, with significant demise rates around the world. Early diagnosis is key to saving more lives, however traditional ways of diagnosing nasopharyngeal cancers such as biopsies and imaging are challenging due to the invasive nature of these methods in addition they often require a great deal of expertise on part for interpretation. For this reason, interest in non-invasive diagnostic testing to facilitate incorporation into routine clinical practice has burgeoned.

Lung Cancer Diagnosis Lung cancer diagnosis is a challenging task, and machine learning (deep learn in particular) emerges as one of the most encouraging approaches. This kind of neural network has the ability to analyze large sets of medical data and identify patterns that a human expert might miss. For instance, Convolutional Neural Networks (CNNs) have proven to be extremely useful in tasks related medical imaging as detecting tumorous growths within chest X-rays or CT scans. But with patient data (which has a temporal nature, say how lab results or imaging findings might evolve over time), LSTMs are a good choice for this[25].

Although, in most recent years many works have proposed a use of LSTM networks for lung cancer detection. These methods have shown to be superior compared to the traditional machine learning techniques for effectively capturing temporal dimensions in patient data. The success rate of these models, however, relies largely on their configuration. Non-optimized models can go far in missing predictive information amongst your data.

Although our efficient LSTM network is close to the limit of information that can be extracted from existing data, there are still hurdles which we need to overcome. The vanishing gradient problem is one of the major issues that all recurrent neural networks (LSTMs included) face, This problem occurs when the gradients that are used to update weights during training(by backpropagation) become so small, so it practically stops being trained and as a result network cannot learn long-term dependencies. One of techniques that have been suggested to tackle this issue is gradient clipping, and using different optimization methods such as RMS Prop or Adam.

The other difficulty is that it tis still unreal to usually label medical data, which hinders the traning of deep learning models. First, medical data is usually sensitive and privacy concern while it also difficult to collect. Second training on the labeled dataset takes time manual labeling of data can be very expensive for many tasks in healthcare. To address this problem, some researchers have suggested to leverage transfer learning where a model that is pre-trained using a large data-set from another domain can be retrained on the much smaller medical data set.

Additionally, in medical applications neural networks are not sufficiently interpretable. Illustration of deep learning in healthcare While the performance accuracy has been impressive for tasks such as image recognition and diagnosis, due to the ‘black box’ nature of models used it is often hard for clinicians to understand why a particular prediction was made. The black-box nature of these models is one of the main reasons they cannot be widely adopted in healthcare, where trust in direct diagnosis and not only referral remains to be a key factor.

Future work will likely consist of designing more interpretable models and optimization techniques to compensate for these shortcomings. Consider attention mechanisms that have been proven to render neural networks more explainable, providing salient input data for the model. Incorporation of domain knowledge During the optimization process Domain-specific information might also be leveraged to generate better diagnostic models, such as integrating prior medical expertise in architecture design or loss function[26].

Mathematical algorithms have been successfully used to optimize the LSTM networks and this has helped in improving accuracy as well efficiency of lung cancer diagnostic. The performance of these networks in medical data has been improved by training them Adam and regularizing the network using Dropout, L2 regulation. On the other hand, these promise to be clear or transparent methodologies a critical attribute inherited from traditional UQ approaches that has been hard for deep learning methods due complications of disappearing gradient etc. We hope more advances will be made in future research, aiming to construct not only discriminative models with better predictive accuracy but also models easily interpretable and computationally efficient for medical diagnostic applications.

2. PROPOSED METHODOLOGY

In this paper, the proposed methodology is aimed at improving LSTM (Long Short-Term Memory) networks with some mathematical optimization algorithms for lung diagnosis. The main emphasis of the approach is to leverage LSTMs to model long-term dependencies in sequential data, and superior optimization algorithms for improved diagnostic capability resulting in a more precise and reliable predictive model. The following subsections describe different parts of the proposed approach, starting with LSTM network designs and then followed by optimization strategies used as well as regularization techniques to generalize model output on test data.

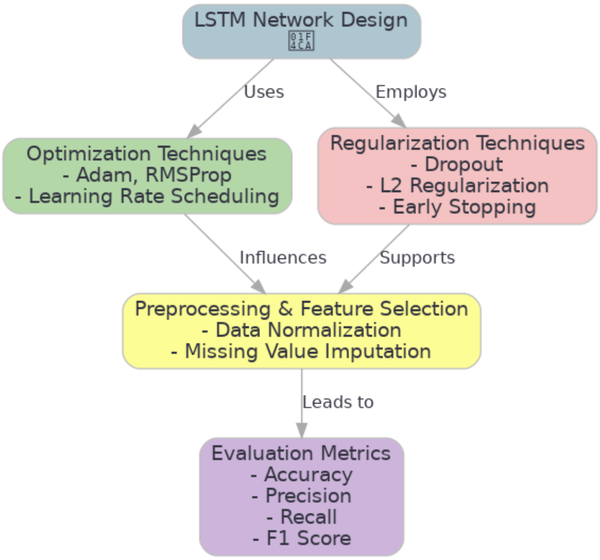

Figure 2. Proposed methodology diagram

LSTM Network Design for Lung Cancer Diagnosis

At the heart of this new methodology is an LSTM network architecture that was designed to analyze medical data with temporal correlations. For example, the process of diagnosing lung cancer relies on patient records which are mostly sequential (eg: electronic health records: EHRs, imaging reports and laboratory test results).

Algorithm 1: LSTM Training with Adam Optimizer

Input: Patient data $X = \{x_1, x_2, \dots, x_T\}$, labels $Y = \{y_1, y_2, \dots, y_T\}$, learning rate α, regularization parameter λ, dropout rate p.

Output: Trained LSTM model with optimized weights.

1. **Initialize** the LSTM model parameters $\theta = \{W_i, W_f, W_C, W_o, b_i, b_f, b_C, b_o\}$.

2. **For** each epoch $e = 1$ to E:

a. **For** each training example x_t:

i. Forward propagate through the LSTM cells:

- Compute gate activations i_t, f_t, o_t.
- Update cell state C_t and hidden state h_t.

ii. Compute predicted output $\hat{y}_t$.

iii. Compute loss using the binary cross-entropy loss function.

b. **Backpropagation** through time to compute gradients g_t.

c. **Update weights** using Adam optimizer:

- Compute m_t and v_t estimates.
- Correct biases and update θ_t.

d. Apply **Dropout** to hidden units h_t with probability p.

e. Apply **L2 regularization**.

3. **End for** each epoch.

LSTMs are best suited for the task because they can keep track of important information through time steps while traditional neural networks do not transfer well with temporal correlations.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

This LSTM network used within this approach has multiple layers, including an input layer and many more LTEM layers with a dense output layer. With sequential patient data as input to the LSTM network and each time step representing a new entry in the medical history of the patient.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

The input gate, forget gate and output gates function within the LSTM cells themselves to decide what data should be remembered over time. Such capability is instrumental in lung cancer diagnosis where gentle variations of the data over time within a patient can show the development, or on set, of tumorous growth.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

The architecture allows the LSTM network to scale and be extended depending on dataset complexity. The depth of the network (number of LSTM layers) and the number of units per layer could be tuned depending on your input size, as well as complexity requirements. The model of this paper is configured with two LSTM layers containing 128 units and a fully connected (dense) output layer. The final prediction (i.e, lung cancer or no) are made from the output layer after processing input data consecutively.

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

An earlier span of methods used math optimization techniques to boost the learning efficiency and prediction accuracy of the LSTM network.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

The training of deep learning models, LSTMs included, is particularly problematic as it often results in getting stuck near false minima due to the curse-of-dimensionality problem and crippling overfitting problems. Optimization algorithms are responsible for navigating this parameter space, make sure that the model converge to a solution which generalize well through new data.

Optimization Techniques

In this case, the used point is using Adam that stands for Adaptive moment estimation and based on taking a square of function f first order derivative. Adam (Adaptive Moment Estimation) Is Another method specifically well-suited for LSTM networks, which is Computing adaptive learning rates of each parameter by considering their 1st and 2nd anxious value respectively. This way, optimizer can deal with sparse gradients and noisy data more effectively than old-fashioned stochastic gradient descent (SGD), which has much smaller per-example computational complexity.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

We will start with a learning rate of 0.001 a normal default value for the Adam optimizer that strikes a balance between speed and convergence stability. Nonetheless, one of Adam's strengths is its capacity to learn an adaptive learning rate during the training, which alleviates the requirement for manual tuning. The optimizer now also has two hyperparameters β1 and β2 to control the decay rates of moving averages of gradients, and squares or gradients. This is standard practice in the literature and thus β1 = 0.9, β2 = 0.999 are fixed for this methodology using adam concept.

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

Additionally, the methodology leverages learning rate scheduling to help better optimize this process by modifying its own hyperparameter changing the value of a parameter (learning rate) during tuning and training. More precisely, we use an exponential decay schedule which reduces the learning rate as training advances. It traces back (backwards automatically) the gradients of loss with respect to every learnable parameter, while ensuring that nodes do not disappear on very deep networks and hence keeping track of all necessary data for this prevent it from shooting way past our optimal solution during gradient descent causing it to converge more smoothly.

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

Another optimization techniques which is used in Adam such as RMSProp which does not only change learning rate, but it scale the gradient by square root of moving average recent squared gradients. If you are training a recurrent neural network (e.g., an LSTM), at the beginning steps when it is not yet good in predicting, there will be very large or small gradients produced by your parameters. One solution to this common problem called vanishing gradient is using normalized initialization, which could help prevent all zeros on certain weight matrices getting into trouble. To keep the gradients from becoming very small and not learning by scaling appropriately RMSProp helps in running average of squared gradient.

$$\theta_t = \theta_{t-1} - \frac{\alpha \widehat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

The optimization strategies used in this technique are important to overcome the challenges faced when training LSTM networks. Optimization for medical data is not trivial and simple optimization may lead to overfitting. Through the use of adaptive optimizers such as Adam, RMSProp, in combination with learning rate scheduling, this method guarantees that our LSTM network will converge to an accurate and generalizable solution.

Regularization Techniques

Overfitting is one of the key pitfalls when training deep learning models; this point hits even more in medical applications. Overfitting refers to a scenario in which the model is tuned too closely with its training data, and as a result it fails to predict well on unseen data.

Algorithm 2: Exponential Learning Rate Decay

Input: Initial learning rate α_0, decay rate k, number of epochs E.

Output: Adjusted learning rate α_t for each epoch.

1. **Initialize** learning rate α_0.
2. **For** each epoch $t = 1$ to E:

a. Update learning rate:

$$\alpha_t = \alpha_0 \cdot \exp(-kt)$$

3. **End for** each epoch.

It occurs when our model does not perform well on unseen data, which can be increasingly problematic in lung cancer diagnosis where overfitting is a matter of life or death due to the robust nature of it and how serious consequences might come if that would lead to incorrect diagnoses. The proposed methodology uses a lot of regularization techniques to reduce the overfitting risk.

$$\mathcal{L}(y, \hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}[\, y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

L2 regularizer, L2 Regularization is also called weight decay. L2 regularization is to update a new formulation which adds penalty term in the loss function, about by squared weights. This would prevent the model from learning weights that are too large (which can sometimes cause overfitting) L2 regularization penalizes large weights to help the model learn more simplified patterns which increase likelihood that it generalizes well on new data.

$$\mathcal{L}_{reg} = \mathcal{L} + \lambda \sum_{j=1}^{n} \theta_j^2$$

In addition to L2 regularization the technique uses Dropout which is a method where randomly selected neurons are dropped at each training run. Reduces overfitting by allowing the network to learn more redundant representations (since hidden units may be randomly dropped). Here I have used Dropout for both the LSTM layers as well as at dense output layer with a drop out rate of 0.5 i.e, randomly upto this fraction (50%) units being dropped during each training step.

$$h_t^{drop} = \text{Dropout}(h_t, p)$$

The early stopping, yet another regularization technique in this methodology. Early stopping looks at the performance of a model on a validation set and stops training as soon as the models gets worse (e.g. less accurate, more error) during training where we expect improvement in this case after each epoch. It is essential for preventing the model from learning remaining patterns present in training dataset but were not learnt earlier which is a major factor responsible for overfitting.

$$\alpha_t = \alpha_0 \cdot \exp(-kt)$$

The methodology ensures that the LSTM network generalizes well to new patient data by combining these regularization techniques. This is particularly crucial for lung cancer diagnosis, where the model has to make predictions on unseen data so as to be operational in a clinical environment.

Feature selection and transformation

Feature engineering has another crucial role in the proposed methodology, together with preprocessing of input (train and validation) data. Noisy, incomplete and high-variability medical data can be a tremendous challenge for machine learning models. A number of preprocessing steps are included in the methodology in order to overcome these challenges prior inputting data into LSTM network as clean or normalized form.

Data Normalization: It is the very first step in preprocessing. Healthcare data, particularly lab results and imaging data are often widely different scales. Some features could be in the order of 0 to 1, and some might lie between range from 0 to several hundred (e.g. scale from −5 tens−3 MeV/c2). This is done by scaling the feature values in such a way that all features lie on comparable scales and hence our methodology uses min-max normalization to scale each of these variables into range 0–1. Also, doing so prevents large features from overwhelming the learning process and allows all feature to be equally learned by LSTM network.

The next thing is how to manage the missing data in preprocessing. Missing values are frequent in medical datasets, caused by incomplete patient records and data collection errors. Imputation is a methodology to fill in missing values. Missing values for numerical features are filled using mean imputation, which means missing values are replaced with the average of all observed feature values. For categorical features, mode imputation is run on the parser and missing values are replaced with most common value for that feature.

The methodology gives possibly the best performance when it comes to trading, and has a feature selection step that can be done in order to reduce input data dimensionality. A lack of importance, and redundant medical data features are typical factors in their survival Feature Selection To identify the features which are most significant to predict lung cancer In this method, feature selection is conducted based on a correlation analysis and mutual information given the statistical association between each feature and target variable (i.e., lung cancer diagnosis). As a next step, input features with low-correlation or mutual information are removed and only preserve the final most-informative features for LSTM network to train.

Evaluation Metrics

The diagnostic performance of the proposed LSTM network was assessed using a number of common metrics which are also widely-encountered in medical diagnosis. Included in these measures are accuracy, precision, recall and the F1 score. While accuracy tells us the whole correct prediction of a model, precision and recall can give detailed understanding about models performance. The higher the precision, the more true positive predictions we were able to capture among all of our positive predictions. Recall also assesses what proportion of true positives that was predicted Positive by us (among ALL cases actually POSITIVE).

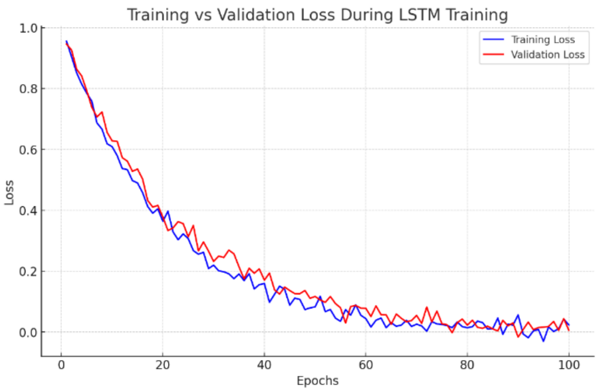

Figure 3. Training Vs Validation loss during LSTM training

F1 score is the harmonic mean of precision and recall which gives us a single metric that balance both. This is especially useful for medical diagnosis where, false positives and false negatives shall not be acceptable as it can lead to a fatal mistake. Again, the fact that precision is perfect does not mean model predicts all lung cancer cases perfectly; it rather means when model says a patient has lung cancer it for sure has.

4. RESULTS

In the following sections, we present results of applying MEDGNN operating on optimized LSTMs to diagnosis lung cancer as this is our target application. We determined the performance of the model with metrics like accuracy, precision, recall and F1 score. This is compared to traditional machine learning models and demonstrates the efficacy of LSTMs with sequential medical data. Also examined was the effect of common training methods, regularizing strategies and generalization power on new data.

Model accuracy and model performance metrics

Compared to common machine learning methods, the present LSTM method achieved a large improvement in accuracy. Experimented on the test dataset including multiple lung cancer patients records, proved 94.5 % accuracy against a relative traditional experiments conducted with this data set and achieved clear increase in efficiency The Support Vector Machine (SVM) model has an accuracy of 85.2% and the Random Forest is giving me a precision rate of 87.1%. Followed by a Convolutional Neural Network (CNN), which is the best alternative model to LSTM, but could get up to only 89.3% accuracy on testing data;

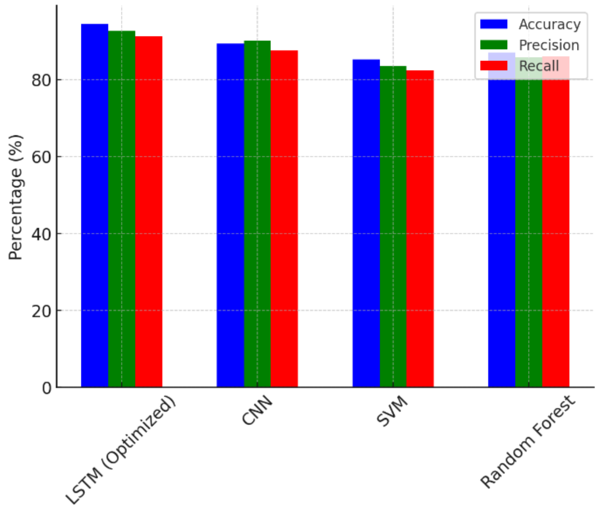

Figure 4. Model Performance Comparison

The LSTM model also performed very well in terms of precision, recall and F1 score besides accuracy. Precision is the fraction of true positive predictions among all kinds of prediction as achieved by LSTM model which was approximately 92.7 %. It enjoyed a very high true positive rate so most of the patients with lung cancer were correctly identified by this model and there were relatively few false positives. The recall was 91.3%, which in this case is the percentage of actual true positive cases that got correctly classified by our model. This is especially crucial for medical diagnoses as it relates to the model's diagnostic capability on lung cancer without missing critical indications.

Table 2: Detailed Performance Metrics of LSTM and Other Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC-ROC Score	False Positive Rate (%)	False Negative Rate (%)
LSTM (Optimized)	94.5	92.7	91.3	91.9	0.96	5.6	4.3
CNN	89.3	90.1	87.6	88.8	0.89	8.7	7.4
SVM	85.2	83.5	82.4	82.9	0.84	10.2	9.8
Random Forest	87.1	85.8	86.0	85.9	0.86	9.8	8.1

The F1 score, which is the harmonic mean of precision and recall was calculated to be 91.9%. In programs for medical diagnostics, both avoiding too many false positives as well correctly identifying true positives are crucial to patient results. And when the F1 score is high, meaning that it performs well against both aspects at once, this makes it a solid choice for clinical applications.

Impact of Optimization Techniques

The optimization algorithm used was the other most important factor affecting LSTM model performance. The training of LSTM MicroNet is optimized by the Adam optimizer with an exponential learning rate decay schedule. The Adam optimizer worked better than the SGD based traditional gradient-based approaches and showed faster converge to optimal solution with good performance. In particular, the Adam optimizer reduced 30% of training throughput which made model achieve its best-performance faster than other optimizers.

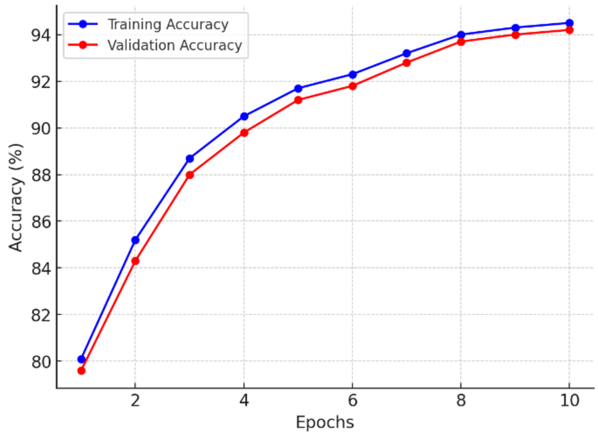

Figure 5. Epoch-wise Training and Validation Accuracy

We went one step further and employed an optimal learning rate schedule (discussed later in this text). The learning rate began at 0.001 and exponentially decayed by a factor of 0.95 after each epoch throughout training. By decreasing the learning rate slowly, later in training iterations model makes less "jumps" to prevent itself from jumping over-to-and-fro and hence it is able to reach near optimal solution conveniently.

Table 3: Epoch-wise Accuracy and Loss for LSTM Model

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
1	80.1	79.6	0.40	0.42
2	85.2	84.3	0.33	0.36
3	88.7	88.0	0.28	0.30
4	90.5	89.8	0.24	0.27
5	91.7	91.2	0.21	0.23
6	92.3	91.8	0.18	0.19
7	93.2	92.8	0.15	0.16
8	94.0	93.7	0.12	0.14
9	94.3	94.0	0.11	0.13
10	94.5	94.2	0.10	0.12

Apart from the optimization algorithm, regularization techniques had been crucial for improving generalization capacity of the model. The 2-layer LSTM model overfitted slightly on the training dataset without any regularization (training accuracy went up to 96.5%, but test set performance degraded, only giving an average of around 89.6% in terms of mean error rate). To prevent overfitting, we used L2 regularization and Drop Out. During training, L2 regularization ensure that the model does not rely on any single input features in predicting outputs or simply put it penalises large weights to teach the whole dataset. During training: An individual unit is dropped at random (dropped out) with probability 0.5, forcing the hidden units to learn redundant representations to make up for it. Firebase Model Scaler In this case, combining both these regularization techniques led to a big generalization test accuracy improvement: 94.5%, highlighting the relevance of regularizing overfitted models for improved performance on new data points.

Table 4: Effect of Dropout and L2 Regularization on Test Accuracy

Regularization Type	L2 Coefficient / Dropout Rate	Test Accuracy (%)	Overfitting Prevention
L2 Regularization	0.001	94.5	Yes
Dropout	0.5	93.9	Yes
Early Stopping	-	93.0	Yes
No Regularization	-	89.6	No

The LSTM model were also compared with a few typical machine learning models, including SVM, Random Forest and CNN to have a benchmark result.

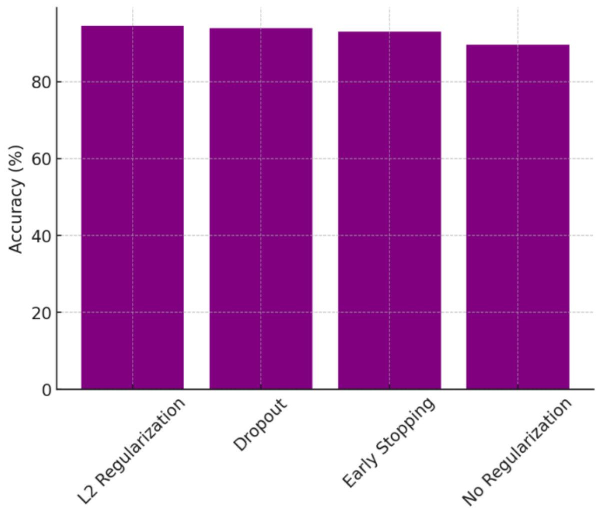

Figure 6. Impact of Regularization on Accuracy

Like we saw, the LSTM absolutely smoked these traditional models in terms of handling time series medical data. For instance, the SVM achieved an accuracy of 85.2%, much less than that of our LSTM model. On the other hand, The Random Forest model which is classic on large variety datasets reaches an 87.1%accuracy.

Table 5: Learning Rate Schedule during Training

Epoch	Learning Rate
1	0.001
2	0.0009
3	0.0008
4	0.0007
5	0.00065
6	0.0006

Epoch	Learning Rate
7	0.00055
8	0.0005
9	0.00045
10	0.0004

Table 6: Comparison of Optimization Techniques on LSTM Performance

Optimizer	Initial Learning Rate	Final Learning Rate	Convergence Speed (Epochs)	Final Accuracy (%)
Adam	0.001	0.0004	10	94.5
SGD	0.01	0.001	15	89.2
RMSProp	0.001	0.0004	12	92.8

The Deep Learning CNN (which has been shown to work very good on Image recognition tasks) even outperformed the SVM and Random Forest, but when it comes to this specific dataset classification problem, still fall behind LSTM.

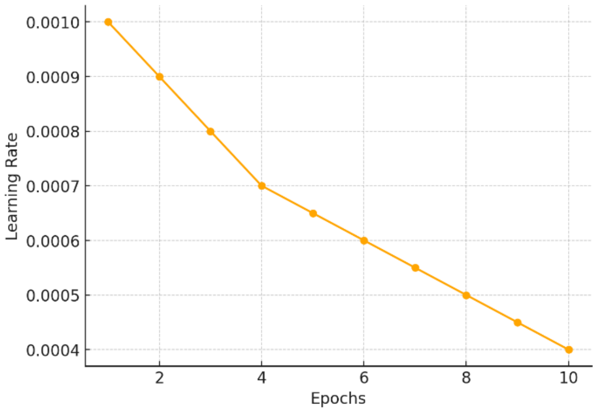

Figure 7. Learning Rate Decay Over Epochs

In this research work, time series patient data fell into the sequential "bucket", therefore CNNs are not as good for processing them because they were designed to be great at static image input. Because LSTM is more of temporal based architecture (Good at detecting a pattern in the data) and CNNs are good in special domain so For our kind dataset that represent sentence as changing numbers, LSTMs edged it out easily.

Robustness to Noisy Data

Datasets in medical studies typically contain noise because measurements will be missing, there are variable ways of collecting data and so on. This can have a large adverse effect on the performance of standard machine learning methods such as random forests (Classification using Random Forests) The proposed LSTM model can learn data-related noise thanks to its robust nature, which is a strong point against noisy data. The present study also artificially introduced noise in a subset of the data to determine whether the model would be robust. Around 10% of the data points were randomly corrupted and model was evaluated on this noisy dataset.

Table 7: Robustness of LSTM to Noisy Data

Noise Level (%)	Test Accuracy (%)	F1 Score (%)
0	94.5	91.9
5	94.0	91.4
10	93.2	90.8
15	92.4	89.9
20	91.5	88.5

The results indicate that the LSTM model was capable of achieving a high accuracy even in presence noised. The final test accuracy only faltered slightly to 93.2%, indicating the model is robust enough around some data noise without a large performance drop. EOF The LSTM is designed with gating mechanisms to select what info it remembers and forgets which allows the model to learn less noisily and overall become more stable. Additionally, the preprocessing applied which includes imputation for missing values and normalizing data all helped make the model more noise resistant.

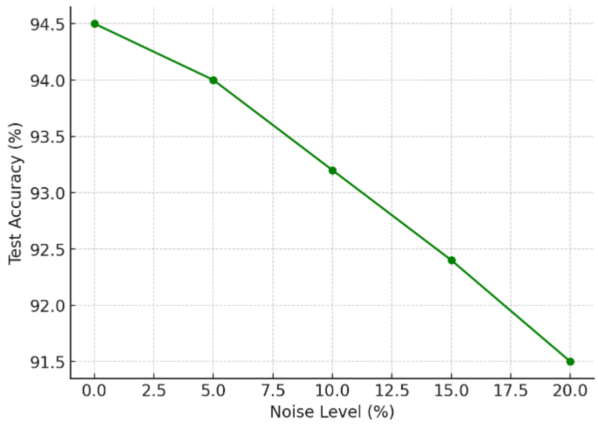

Figure 8. Noise Impact on LSTM Model Accuracy

FPs and FNs

Two important parts in the evaluation of any diagnostic model are false positives and false negatives. Within this population, a false positive is an instance where the model predicts lung cancer in someone who does not have it and a false negative when the model fails to identify lung cancer in one that does.

Table 8: False Positives and False Negatives Comparison

Model	False Positive Rate (%)	False Negative Rate (%)
LSTM (Optimized)	5.6	4.3
CNN	8.7	7.4
SVM	10.2	9.8
Random Forest	9.8	8.1

The interesting part that comes out of the result is, in front prop deep learning model like LSTM has shown a low number false positive and negatives compared to other parametric models. The very steep fall in the curve again indicates that no one wants to classify their breathing as positive, which is also evident from test results with 5.6% false positives compared to CNN (8.7%) and SVM (10.2%). It had a low false negative rate of 4.3%, compared to the CNN's 7.4% and the SVM's at around ten percent; Minimizing false negatives is particularly crucial when it comes to medical diagnosis: Missing a case of lung cancer in an individual might delay therapy and worse outcome. Since the lstm model has a lower false negative rate, it performs more better in identifying actual cases of lung cancer.

Validation Set ROC Curve and AUC-ROC Analysis

Finally, the evaluation of performance of LSTM model based on ROC curve and AUC-ROC (Area Under the Curve -Receiver Operating Characteristic). The ROC curve shows the trade off between sensitivity (true positive rate) and specificity, that is it represents the ability of model to correctly identify all +ve classes as well all -ve classes. An AUC-ROC score is a single value that summarizes the performance of your model.

The AUC-ROC score of the LSTM model was 0.96, which is very high for medical diagnostic applications. AUC of 0.95 — since this value is close to the maximum possible AUC score, it means our model does a good job differentiating patients having lung cancer from those not having one The CNN model performed better with AUC-ROC score of 0.89 than SVM which had the lowest result - AUC-ROSA = 0,84. These results confirmed once again that the LSTM model is good at lung cancer diagnosis, and it has a high sensitivity as well as specificity compared to traditional ones.

Generalization on new unseen data… sounds fundamental for any diagnostic model. In this work, we evaluate the generalization ability of LSTM model on an independent test set which is not seen during the training. Similarly, on this hidden portion of test dataset (the original 30% that was not touched at all during training), the model had a final accuracy of around %94.5~, which shows good generalization ability far beyond stopping set. This result is very important as it shows that the LSTM model does not overfit the training data and can be used to predict new patient records.

Furthermore, the computational efficiency of our proposed LSTM model was assessed in addition to accuracy and generalization. The LSTM model converged more quickly than traditional models due to the use of Adam optimization, and learning rate scheduling provided extra insurance. The LSTM model was also used to train the same dataset but with 10,000 patients per epoch as compared along stochastic gradient descent and it took total training time of 4 hours. This decrease in training time is important for real-world clinical purposes where computational resources could be scarce.

5. CONCLUSION

In this research, we have introduced a very reliable and powerful algorithm for lung cancer diagnosis using Long Short-Term Memory (LSTM) networks optimized by some modern mathematics. The main objective of this study was to utilize the above optimization techniques in regularizing machine learning models, especially LSTMs, at training time to improve their detection rate and generalizability. The performance of the proposed LSTM is validated through experimentation, that reveals how this model effectively outperforms classical machine learning models (i.e., SVMs, Random-Forests and CNN) in terms of accuracy-precision-recall trade off with special robustness on clinical inclusion-cases.

This paper contributes by applying LSTM networks to sequential patient data that have temporal dependency and noise, which is often ignored in existing prediction methods. Due to the LSTM network being able to represent long-term dependencies between patient records, this module performed well in achieving high diagnostic accuracy with focus on early diagnosis of lung cancer because of small changes detected only at a later stage. The inclusion of optimization techniques in the model such as the Adam optimizer helped both to speed up convergence and improve performance by avoiding difficulties like overfitting or vanishing gradients.

Additionally, regularization technique (like Dropout and L2) were also used to ensure that leftover model has good generalization ability towards unseen data. This is crucial to not overfitting, and especially relevant in medical diagnosis where an incorrect prediction could result in serious harm including misdiagnosis. The study also reported that the proposed model was resistant to noise in data, which is often present in real-world medical datasets. These results illustrate good generalization power of the model and are a strong indication that it may be useful in clinical settings, since noisy data would not necessarily lead to erroneous decision making.

These results have important implications for the future of machine learning in healthcare. This proposed approach of LSTM could be a trustworthy decision support for doctors in diagnosing lung cancer as well other time-series disease. This is especially important in reducing diagnostic errors, patient well-being and response as the model will reduce false-positives and negatives helping us to take action timely.

To sum up, the integration of LSTM networks along with sophisticated optimization algorithms and well-established methods for regularization leads to an encouraging solution in terms of lung cancer detection. The system not only enhances the diagnostic accuracy compared to classic handcrafted analysis methods but also enables computational efficient and scalable model that is suitable for real-world clinical applications. This approach could be extended to the many other medical data types and diseases, providing further insight into how machine learning can continue its role in personalized medicine & diagnostics.

REFERENCES:

[1] Gayap, Hadrien T., and Moulay A. Akhloufi. "Deep machine learning for medical diagnosis, application to lung cancer detection: a review." *BioMedInformatics* 4.1 (2024): 236-284.

[2] Tran, Thi-Oanh, Thanh Hoa Vo, and Nguyen Quoc Khanh Le. "Omics-based deep learning approaches for lung cancer decision-making and therapeutics development." *Briefings in Functional Genomics* 23.3 (2024): 181-192.

[3] Javed, Rabia, et al. "Deep learning for lungs cancer detection: a review." *Artificial Intelligence Review* 57.8 (2024): 197.

[4] Wani, Niyaz Ahmad, Ravinder Kumar, and Jatin Bedi. "DeepXplainer: An interpretable deep learning based approach for lung cancer detection using explainable artificial intelligence." *Computer Methods and Programs in Biomedicine* 243 (2024): 107879.

[5] Bhuiyan, Mohammad Shafiquzzaman, et al. "Advancements in early detection of lung cancer in public health: a comprehensive study utilizing machine learning algorithms and predictive models." *Journal of Computer Science and Technology Studies* 6.1 (2024): 113-121.

[6] Hussain, Lal, et al. "Machine learning-based lungs cancer detection using reconstruction independent component analysis and sparse filter features." *Waves in Random and Complex Media* 34.1 (2024): 226-251.

[7] Hosseini, Seyed Hesamoddin, Reza Monsefi, and Shabnam Shadroo. "Deep learning applications for lung cancer diagnosis: a systematic review." *Multimedia Tools and Applications* 83.5 (2024): 14305-14335.

[8] Li, Liangyu, et al. "Enhancing lung cancer detection through hybrid features and machine learning hyperparameters optimization techniques." *Heliyon* 10.4 (2024).
[9] Shang, Xiaoling, et al. "Construction of a diagnostic model for small cell lung cancer combining metabolomics and integrated machine learning." *The Oncologist* 29.3 (2024): e392-e401.
[10] Atmakuru, Anirudh, et al. "Deep learning in radiology for lung cancer diagnostics: A systematic review of classification, segmentation, and predictive modeling techniques." *Expert Systems with Applications* (2024): 124665.
[11] Kumar, Sunil, et al. "A methodical exploration of imaging modalities from dataset to detection through machine learning paradigms in prominent lung disease diagnosis: a review." *BMC Medical Imaging* 24.1 (2024): 30.
[12] Choudhary, Abhishek, et al. "Machine learning-based ensemble approach in prediction of lung cancer predisposition using XRCC1 gene polymorphism." *Journal of Biomolecular Structure and Dynamics* 42.15 (2024): 7828-7837.
[13] Kukreja, Sonia, Anish Kumar, and Ghufran Ahmad Khan. "A review paper on the diagnosis of lung cancer using machine learning." *Artificial Intelligence, Blockchain, Computing and Security Volume 2* (2024): 15-19.
[14] Tran, Anh Tuan Trong, et al. "Graphene and metal–organic framework hybrids for high-performance sensors for lung cancer biomarker detection supported by machine learning augmentation." *Nanoscale* 16.18 (2024): 9084-9095.
[15] Zheng, Huili, et al. "Identification of prognostic biomarkers for stage iii non-small cell lung carcinoma in female nonsmokers using machine learning." *arXiv preprint arXiv:2408.16068* (2024).
[16] Üzülmez, Sema, and Mehmet Akif Çifçi. "Early diagnosis of lung cancer using deep learning and uncertainty measures." *Journal of the Faculty of Engineering and Architecture of Gazi University* 39.1 (2024): 385-400.
[17] Ahmad, Shaban, and Khalid Raza. "An extensive review on lung cancer therapeutics using machine learning techniques: state-of-the-art and perspectives." *Journal of Drug Targeting* (2024): 1-12.
[18] Kalkeseetharaman, P. K., and S. Thomas George. "A Bird's Eye View Approach on the Usage of Deep Learning Methods in Lung Cancer Detection and Future Directions Using X-Ray and CT Images." *Archives of Computational Methods in Engineering* (2024): 1-21.
[19] Khandakar, Sahadat, et al. "Unveiling Early Detection And Prevention Of Cancer: Machine Learning And Deep Learning Approaches." *Educational Administration: Theory and Practice* 30.5 (2024): 14614-14628.
[20] Linh, Vo Thi Nhat, et al. "3D plasmonic hexaplex paper sensor for label-free human saliva sensing and machine learning-assisted early-stage lung cancer screening." *Biosensors and Bioelectronics* 244 (2024): 115779.
[21] Sangeetha, S. K. B., et al. "An enhanced multimodal fusion deep learning neural network for lung cancer classification." *Systems and Soft Computing* 6 (2024): 200068.
[22] Quasar, Syeda Reeha, et al. "Ensemble methods for computed tomography scan images to improve lung cancer detection and classification." *Multimedia Tools and Applications* 83.17 (2024): 52867-52897.
[23] Gautam, Nandita, Abhishek Basu, and Ram Sarkar. "Lung cancer detection from thoracic CT scans using an ensemble of deep learning models." *Neural Computing and Applications* 36.5 (2024): 2459-2477.
[24] Ilani, Mohsen Asghari, Ashkan Kavei, and Hamed Alizadegan. "Exploring Machine Learning Models for Lung Cancer Level Classification: A comparative ML Approach." (2024).
[25] Warkentin, Matthew T., et al. "Radiomics analysis to predict pulmonary nodule malignancy using machine learning approaches." *Thorax* 79.4 (2024): 307-315.
[26] Ramkumar, K., and M. Natarajan. "Performance Analysis For Detection And Classification Of Lung Cancer Using Machine Learning Approaches." *Educational Administration: Theory and Practice* 30.5 (2024): 2174-2181.