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Original Article

Deep Radial Recurrent Feedforward Neural Nets (DRRFNN): A Stacked L2L Learning Model for Lung Cancer Patients' Data

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Abstract *- Artificial intelligence (AI) is one of the latest advances in the early detection of lung cancer. Researchers expect that employing AI to sustain lung cancer detection could complete the methodology faster and more effectively and eventually help to predict more patients at a premature step. Deep learning has been validated as a prevalent and more productive approach in numerous medical imaging diagnosis fields. This research designates the deep learning and python programming language to frame highly accurate lung cancer classification and prognosis. Researchers portray a precise stacked L2L model termed Deep Radial Recurrent Feedforward Neural Nets (DRRFNN). The proposed method DRRFNN manifests adequate attainment on Lung cancer data compared with six existing designs such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRUs), Radial Basis Function (RBF), Deep Belief Network (DBN), Feedforward Neural Network (FNN) and Artificial Neural Network (ANN).*

Keywords *- Lung Cancer, Deep Learning, Python, Classification, Prediction.*

1. Introduction

Cancer is the name of a disease formed due to the abnormal growth of tissues in the human body. The disease is one of the most common prominent diseases that endanger human wellness [1]. There are 100 varieties of cancer, and the most significant life-threatening tumor is lung cancer. The current calculations presented by the World Health Organization (WHO) show that almost 7.6 million deaths are due to lung cancer worldwide. Furthermore, in 2030 the worldwide of humankind is conjectured to extend by 17 million of this disease. While unnatural cells separate in an unlimited way to form a growth in the lung is lung cancer. The foremost manifestations are cough, breathlessness, and weight loss, and the remedies are surgery, chemotherapy, and radiotherapy. The disease begins in the windpipe (trachea), the main airway (bronchus), or the lung tissue. There live 2 chief kinds of lung cancer: non-small cell lung cancer and small cell lung cancer. Passive smoking too develops the endanger. In aged people, lung cancer is more found, and in many people with earlier chest predicaments or lung illnesses like emphysema, this disease was common. The other danger factors are contact in the workplace, vulnerability to radon gas, air contamination, and chemicals. Primary lung cancer means the cancer origins in the lung and when that disease commences into another portion of the body implies secondary lung cancer. The spread and size of the tumor indicate the stage. Early-stage cancer is miniature cancer and can treat it early, while cancer flattened into neighboring tissue denotes advanced-stage cancer. The doctor prescribes an operation if the cancer is in the early stage, which means removing the affected spot. If the patient's health is inadequate for surgery, radiotherapy to kill the cancerous cells may be suggested. In the advanced stage, doctors recommend operation or radiotherapy and chemotherapy. There are additionally several medicines named targeted therapies. It helps a specific difference in the growth of the cells, and it can delay the process of spreading. The only scheme for curing lung cancer is in the early stage, by making signs and behaviors inconvenient information that can be used to simulate the presence of disease [2]. At all times, this cancer doesn't show the indications in the beginning stages. Sometimes people may blister fingers and nails (finger clubbing), which hurts and causes inflammation in their joints. The aforementioned is hypertrophic pulmonary osteoarthropathy (HPOA). A unique class of lung cancer arising right at the top of the lung indicates a Pancoast tumor. Here let, the symptom is shoulder discomfort or pain that moves down to the arm. At the same time, pressing or damaging the tumor in the nerve that travels up from the neck to one side of the face that condition to be Horner's syndrome.

The strategies of deep learning methods drive lung cancer early prognostication and symptomatic research at the beginning stage [3]. Machine learning handles easier thoughts; the field of deep learning runs with artificial neural networks and schemes whereby humans think and learn. Continuously freshly, neural networks are bounded by computing strength and restricted in complexity. Nevertheless, improvements in Big Data analytics have allowed larger, advanced neural networks, permitting computers to examine, study, and respond to complicated situations more quickly than people. Deep learning assisted image classification, language translation, and speech recognition. It determines all pattern recognition queries in the absence of human interference. The neural network designs are layers of nodes like people's brain neurons. Nodes inside discrete layers connect to neighboring layers. A network is said to be deeper based on a number of layers. The individual neuron collects thousands of signals from further neurons.

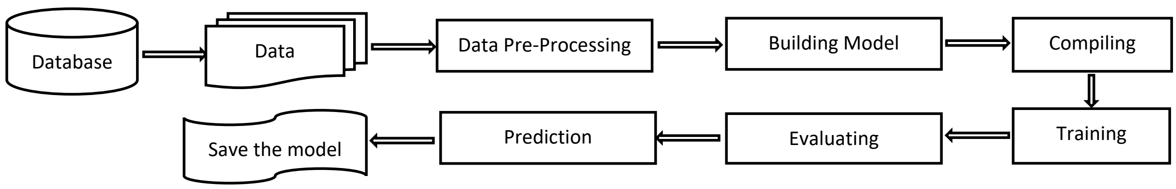


Fig 1. Block diagram of DL methodology for Lung Cancer model

There indicate weights for traveling between the signals and nodes in the artificial neural network [4]. A larger weighted node will use a higher influence on the following layer of nodes, and the layer accumulates the weighted data to provide an output. Deep learning operations need potent hardware then. Only they can treat a massive volume of data for complicated numerical computations. Yet, despite the before-mentioned excellent hardware, some deep learning practice calculations maybe need weeks. Figure 1 represents the steps of the deep learning methodology for getting highly accurate classified lung data. Database, Data, and Data Pre-processing define in the Materials section. The following section clarifies the Building Model, and module IV covers the Evaluation for calculating model evaluation metrics. Section V explains the prognosis of lung cancer data by a highly precise proposed Stacked L2L model: Deep Radial Recurrent Feedforward Neural Nets (DRRFNN), and the final section, bears a conclusion.

2. Materials

2.1 Database and Data

A database is a standardized gathering of structured knowledge or data saved electronically in a machine. It is normally dominated by a database management system (DBMS). Data in the usual kinds of databases running now is typically designed in rows and columns in a set of tables to perform processing and data questioning efficiently. Then it will be quickly accessed, survived, altered, renewed, handled, and secured. Congregating information is the superior level of the methodology. Data is consolidated from the different databases or references and the variety of data accumulated in the wished plan model. The gathering aims to identify and obtain all problems. The quantity and quality of data decide the effectiveness of the result.

The lung cancer data is solicited from the cancer data world database. Some lifestyle routines can boost the venture for lung cancer. The input accommodates lifestyle risk circumstances of lung cancer. Deep learning can resolve approximately whatever dilemma of machine perception, including sorting, clustering, and prognostications concerning it. Keras is a high-level deep learning API running on top of TensorFlow, a machine learning/deep learning framework [5]. It furnishes a comfortable, modular, and systematic interface to crack deep learning issues. Importing the Keras libraries and Data Loading is the initial stage for sporting a deep learning problem. In the Keras model, the raw data cannot be straight processed so that the data is altered into an appropriate structure to facilitate the design to analysis.

2.2 Data Pre-processing

In the pre-processing stage, data convert into an understandable format [6]. The first step is clearing the dataset of null values. Then, employ encoding to convert categorical values into numerical values. Next need to separate the dataset into training and testing. Eventually, scale the dataset the coverages from -1 to 1. Manipulating MinMaxScalar standardization allows orienting the design satisfactorily and permits it to assemble more manageable. Figure 2 is a visual presentation of a correlation matrix describing the correlation between distinct variables [7]. Correlation is a phrase used to define the statistical calculation of a linear relationship between two variables. When there are numerous variables and the intent is to encounter a correlation between them and accumulate them operating a suitable data structure. That matrix data structure is called a correlation matrix**.** The correlation coefficient value can catch any values from -1 to 1. The value stands at 1, and it is displayed as a positive correlation between two variables, which suggests that both variables are increasing. If the value is -1**,** it is stated as a negative correlation. This indicates that when one variable increases, the other variable decreases. When the value is 0, then there is no correlation between them. This implies that the variables modify arbitrarily with each other. Comprehend the linear affinity between predictor values to specify multicollinearity. In the training time, when the values arrive greater than 0.7 or less than -0.7, one of the variables terminates as a predictor value. With the existence of predictor variables keeping multicollinearity, the coefficients of the predictor values in the design can be unreliable.

Fig 2. Heatmap for correlation

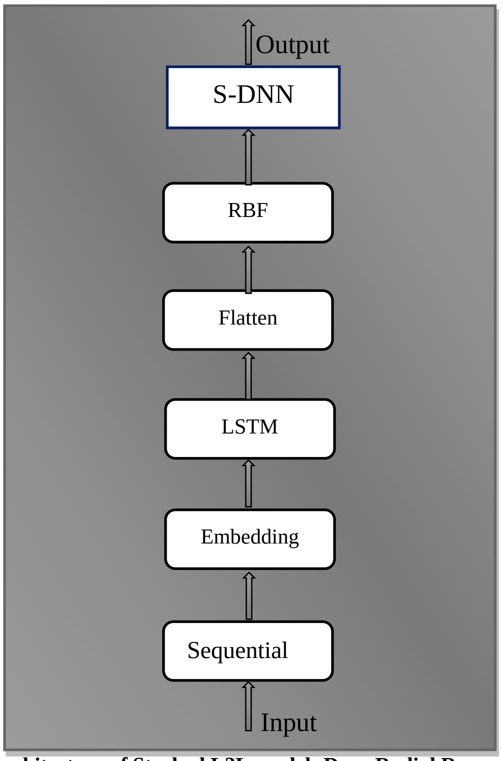


Fig. 3 Architecture of Stacked L2L model: Deep Radial Recurrent Feedforward Neural Nets (DRRFNN)

3. Building Modeling

Artificial Intelligence frameworks are mathematical algorithms that utilize data and professional human input to reproduce a conclusion an expert would make when delivering that identical knowledge [8]. Building modeling decides the query category in the outcome; hereabouts, the situation is for accomplishing classification, and the dataset is labeled; consequently, the supervised techniques were hired. This section preys to generate a deep learning model to analyze numerous classifiers' data for better accuracy [9]. The research studied six existing classifiers compared with the proposed work [10]. A neural network is a computational design that is constructed employing stimulation from the functioning of the human brain [11]. Building a deep learning system stipulates three-layer types: Input, Hidden, and Output layers. The input layer inputs the data and delivers them to the hidden layers. No computation occurs in this layer. There were some layers called hidden layers that stayed between the input layer and the output layer. These coatings function the computations and provide the report to the output layer [12]. Figure 3 displays the architecture of Stacked Layer to Layer(L2L) proposed called model Deep Radial Recurrent Feedforward Neural Nets (DRRFNN). The research constructs a stacked-layer to layer model with Sequential, Embedding, Long Short-Term Memory (LSTM), Flatten, Radial Basis

Function (RBF), and Stacked-Deep Neural Network(S-DNN). The input data departs from the sequential layer, where the individual layer has precisely taken the input and delivered the output to the next layer [13]. Then moves, the training from layer to layer, and the result arrive at the end of the training journey through the final layer of S-DNN. Add method adds the next layer of the model on top of the stack.

The sequential layer functions as a series of integers that embeds each integer into a 64-dimensional vector through the embedding layer. It processes the sequence of vectors using an LSTM layer by RNN [14]. The RNN is robust for framing data ordering such as time sequence. This layer operates a for loop to repeat over the timesteps of arrangements while keeping an inner condition that encodes data about the timesteps [15]. Flattens layer flattens the intake, and it does not concern the batch size. Anymore the intakes are shaped (batch) without a segment axis, then flattening adds a supplementary channel measurement, and the outcome form is (batch, 1) [16]. Fully-Connected Feedforward Neural Networks use a radial basis function to activate their hidden layers. In the RBF layer, the gamma value is 0.5, and there are ten units or nodes for training [17]. Describes the stacked Deep Neural Networks(S-DNN) with seven layers utilizing the Dense class of Keras [18]. The dense layer implementation is done with different parameters such as units, shape, activations, and kernel initializers. Each layer has different units or nodes and employs relu, sigmoid, and softmax as the activation functions in the stack. A statistical distribution kernel_initializer help to initialize the weights of the Keras layer with normal distribution [19].

3.1 Compiling

After building the model, the subsequent stage is to compile it. Here the effective backend library such as TensorFlow is used in the compiling time. To illustrate the grid for training and making prophecies, the backend glancingly determines the path to run on the hardware GPU. When compiling, assign more parameters to sufficiently estimate the model and locate the most suitable weights to map inputs to outcomes in data. Here additionally added parameters are Loss function, Optimizer, and Metrics [20].

3.1.1 The Loss Function

When the error is more downward, the design is nearer to the destination. Distinguishable problems mandate different loss functions to preserve a trace of progress. Here for manipulating classification, binary cross-entropy as a loss function is employed.

3.1.2. The Optimizer

The optimization algorithms ameliorate the loss function's adequate outcome. The prevalent version of gradient descent is adam manipulating the research and providing the best output in queries.

3.1.3. Metrics

It evaluates the model. The research work employs accuracy as the metric for Evaluation.

3.2 Training

Besides the triumphant compilation of the design, now prepared to fit the dataset to the system and begin training the neural grid [21]. Requires to specify the epochs and batch sizes over training time. The training procedure will evaluate for a specified number of iterations via the data named epochs; it is just defined in the epochs parameter. Furthermore, set the numeral of dataset rows assumed before the design weights are modernized within per epoch, known as batch size, and specified utilizing the batch_size argument.

4. Evaluation

After successful model training, estimates the performance of the network. This module shows the final level of constructing a Keras deep learning highly accurate model.

Table 1. Experimental Results of Models

Classifiers	Precision (%)	Recall/ Sensitivity (%)	F1-score (%)	Specificity (%)	Logarithmic Loss	Accuracy (%)
LSTM	76.19	69.56	77.27	72.72	9.21	73.33
GRU	90.47	82.60	90.90	86.36	4.61	86.66
RBN	66.66	25	97.91	36.36	4.32	87.5
DBN	80	50	97.91	61.53	3.08	91.07
FNN	80	50	97.91	61.53	3.08	91.07
ANN	70	87.5	93.7	77.7	2.47	92.85
DRRFNN	87.5	87.5	97.91	87.5	1.23	96.42

The training data is delivered to the desired model and then receives a mapping between the input and the output. Once the selected design is trained, the system stays tested by testing the dataset to determine whether the technique functioned sufficiently. Evaluating a system by manipulating the attainment of metric strategy, quality proportions, and matrix estimations [22],[23]. Table 1 illustrates the testing analysis of lung cancer patients' data systems. The analysis operated in the test implementation is Precision, Recall/ Sensitivity, Specificity, F1-score, Log loss, and Accuracy. The observation result obtained from the design evaluation matrix is called the confusion matrix [24]. The calculation of the Precision, Recall/ Sensitivity, Specificity, and accuracy is from some equations via the confusion matrix [25].

$$\text{Precision}=TP/(TP+FP) \quad (1)$$

$$\text{Recall}=TP/(TP+FN) \quad (2)$$

$$F1=2*(\text{recall}*\text{precision})/(\text{recall}+\text{precision}) \quad (3)$$

$$\text{Specificity}=TN/(FP+TN) \quad (4)$$

$$\text{Accuracy}=TP+TN)/(TP+FP+TN+FN) \quad (5)$$

Precision is the number of valid positive outcomes diverged by the number of positive outcomes forecasted by the classifier is represented in formula 1. Formula 2 illustrates a recall, the number of proper positive outcomes diverged by the number of all positive instances. Formula 3 defines the F1 score, implying Harmonic Mean between precision and recall. It has a range [0, 1] and signifies the meticulousness and potential of the classifier. Each model shows accuracy when the precision is high, and recall is low. The model rendition is good when the F1 score is higher. Formula (4) reveals the specificity of the estimation, and it is the ratio of samples that do not carry the lung cancer. Logarithmic Loss performs by penalizing the incorrect classifications. It functions sufficiently for multi-class. When operating with Log Loss, the classifier must allocate the probability to an individual category for all the instances. Log Loss nearer to 0 demonstrates high accuracy, and when the Loss is far from 0, it shows lower accuracy. Commonly, less Log Loss narrates high accuracy for the model. Compared to other existing methods, the research shows the highest accuracy leads proposed model DRRFNN according to its 1.23 log loss.

Formula 5 shows the proportion of accurate prognoses to the whole amount of input instances. The stacked L2L model Deep Radial Recurrent Feedforward Neural Nets (DRRFNN) obtained an accuracy score of 96.42%. Figure 4(a) presents the Area under the ROC Curve (AUC) of an accurate Lung cancer model. AUC calculates the whole two-dimensional region underneath the total ROC curve from (0,0) to (1,1) [26]. When a system predicts 100% false, then the AUC shows 0.0, and if the model prognoses are 100% correct, the AUC depicts 1.0. The proposed model DRRFNN reached the Area under the ROC Curve 1.0 [27]. Figure 4(b) depicts the comparison of models with accuracy. The accuracy of each model perceives during the training stage and compared to obtain the most seductive absolute model [28]. The bar graph is a pictorial illustration of a data visualization technique highlighting the classification. The biggest bar in a bar graph indicates high accuracy compared to a smaller bar. The model LSTM demonstrates very low accuracy compared to other models. Through the graphical analysis, researchers easily comprehended that the models DBN and FNN have the same accuracies. According to this estimation, the proposed work Deep Radial Recurrent Feedforward Neural Nets (DRRFNN), proves highly precise and reliable.

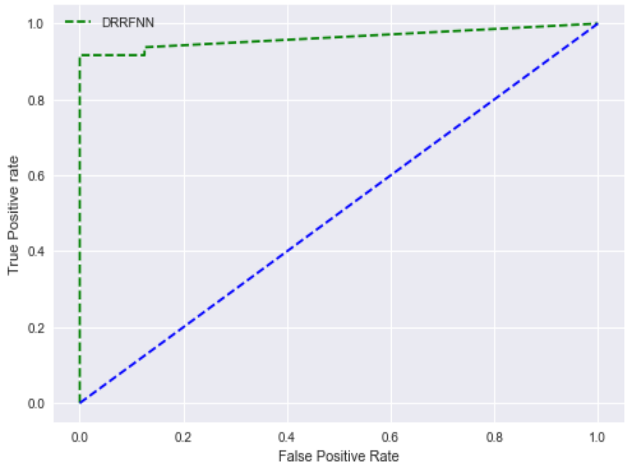
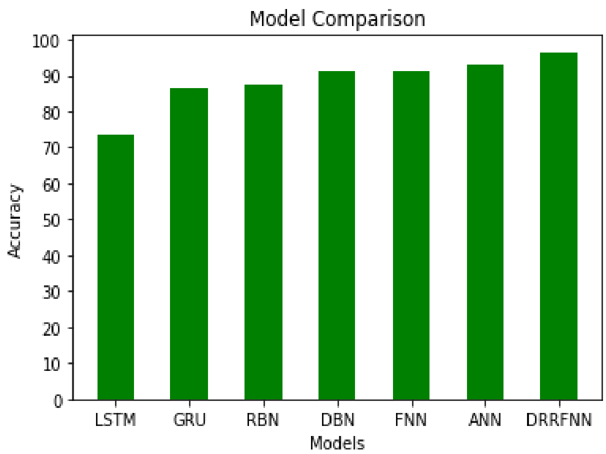


Fig 4 (a) AUC of an accurate Lung cancer model



(b) A bar graph for model comparison with its accuracy

5. Prediction

The last module of DL methodology for the Lung Cancer model is prediction, in which prognosis is the result of data by utilizing predict method [29]. Researchers predict the class for lung cancer data employing finalized classification model Deep Radial Recurrent Feedforward Neural Nets (DRRFNN) in Keras utilizing the predict_classes() function [30]. The accurate Deep Radial Recurrent Feedforward Neural Nets (DRRFNN) forecasts whether the patient has Cancerous: Malignant or Non-Cancerous: Benign. At last, save the exact prediction model

Deep Radial Recurrent Feedforward Neural Nets (DRRFNN) according to the DL methodology.

6. Conclusion

Artificial intelligence is poised to turn a transformational power in healthcare. AI suggests several miracles over conventional analytics and clinical decision-making methods. Learning methods can become more meticulous and accurate as they intervene with training datasets, permitting humans to achieve exceptional insights into diagnostics, care processes, treatment variability, and patient outcomes. The new lung cancer cases continuously decrease due to fewer people smoking and advancements in early prediction and treatment. Currently, deep learning provides an outstanding performance in lung cancer detection, which means Deep Learning is now becoming the key for doctors in the Area of Medical Science. This research uses deep learning principles to learn the data and acquire accurate prophecies. The work process is under a deep learning methodology, and the techniques are executed on the Lung Cancer dataset. The researchers constructed a proposed strategy, the Stacked Layer to Layer(L2L) model Deep Radial Recurrent Feedforward Neural Nets (DRRFNN). The stacked layer to layer model bears stacked layers, which are Sequential, Embedding, Long Short-Term Memory (LSTM), Flatten, Radial Basis Function (RBF), and Stacked-Deep Neural Network(S-DNN). The experimental analysis clarifies that the suggested method achieves high accuracy compared to six traditional methods. Eventually, the analysis arrives at an excellent prediction for the Lung Cancer dataset through the new Deep Radial Recurrent Feedforward Neural Nets (DRRFNN) method. The research acquired a comprehensive model comprehended with adequate, robust, and accurate.

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