

NEURAL NETWORKS

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ABSTRACT

The neural networks review the categories, explaining the organization algorithm techniques required to improve the generalization performance and the Feedforward Neural Network (FNN) learning speed. They are needed to discover the research trends changes under the six categories of the optimization algorithms for the learning rate, learning algorithms which are gradient-free. Metaheuristic algorithms collectively and new research directions are recommended for the researchers to facilitate the algorithm's understanding of the natural world applications to solve the complex engineering, management, and problems in the health sciences. FNN gained research attention for making an informed decision. The literature survey focuses on optimization technology and learning algorithms. The optimization techniques and the FNN learning algorithms identified are segregated into six categories based on the mathematical model, problem identification, proposed solution, and technical reasoning. FNN contributions rapidly increase the ability to make informed decisions reliably.

KEYWORDS

Classification schemes; Optimization techniques; CNN-RNN Model;

1. INTRODUCTION

The Feedforward Neural Network has the capability to extract valuable patterns, and much-informed decisions are made through the high dimensional data. The data would become costly without proper analysis in the business intelligence process. (Awan; Chung; Waqar Ahmed Khan. et al., 2020) In this regard, Machine Learning gains interest significantly to facilitate business intelligence through data analyses, gathering, and knowledge extraction to guide users to make informed decisions. Extensive theoretical information and knowledge would be required for building the FNNs to have the characteristics of the performance of better generalization and learning speed. (Awan; Chung; Waqar Ahmed Khan. et al., 2020) The learning speed and generality play a critical role in deciding the learning algorithms' usage and the optimization techniques for building the optimal FNNs. The drawback with the FNN applicability is that it would become difficult with the inefficient user expertise and theoretical information. The efforts to answer the fundamental questions review the two categories of algorithms for gradient and accessible learning. (Awan; Chung; Waqar Ahmed Khan. et al., 2020) The researcher demonstrates the optimization effectiveness to solve real-world management, health sciences, and engineering problems to enrich the contents, thereby enabling the users to get familiar with the FNN applications.

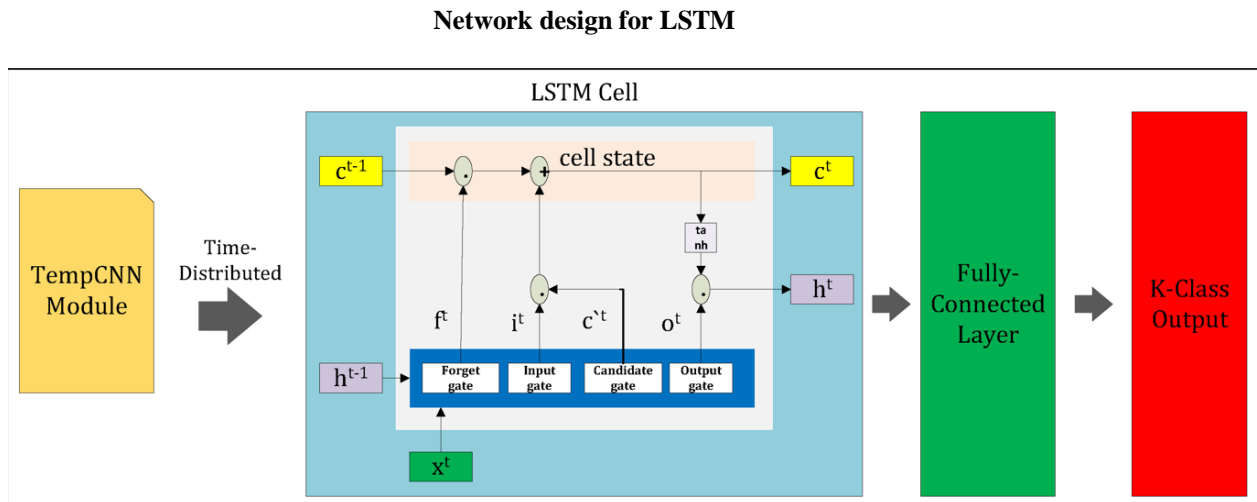
2. DEEP PARALLEL NEURAL (DEEPPN) OVERVIEW

DeepPN addresses the problems of the existing methods through the parallel deep neural network DeepPN. The two deep structures cause the sequence features captured to disappear gradually as the depth increases. DeepPN improves the feature-capturing ability of RNA Binding Proteins

(RBP) sequences. (Gahegan; Lehnert; Liu. et al., 2022) The methods expected under various perspectives capture features that are not similar and complement each other. The formula for RNA sequences is shown below, $H = g_{\text{DeepPN}}(g_{\text{CNN}}(X), g_{\text{ChebNet}}(X))$

3. NEURAL NETWORK DESIGN FOR LONG SHORT-TERM MEMORY (LSTM)

LSTM is adapted to process the sequential input data. The above network captures the long-term dependency on the time series data through the internal state memory cell. (Adhikari; Naetiladdanon; Sangswang. et al., 2022) The above network learns the significant features. The LSTM module's overall architecture is shown in the diagram shown below,

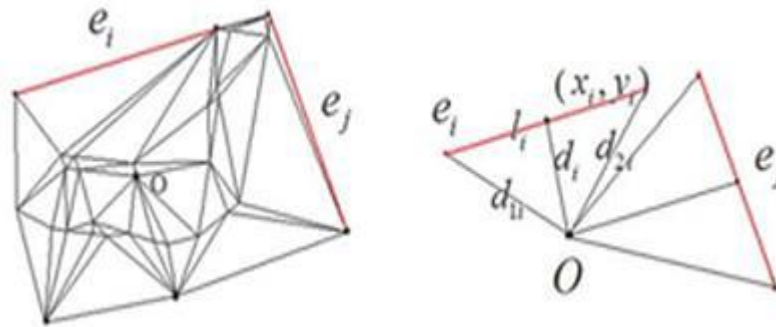


The architecture comprises the input, candidate, forget, and output gates. The LSTM network created from the sequence construction handles the extracted features of temporal correlation. (Adhikari; Naetiladdanon; Sangswang. et al., 2022) The time-distributed technique is adopted to reuse the TempCNN module throughout the input slices. The LSTM layer analyzes the input time sequence and implicit correlation learning between the temporal pieces. The output layer consists of k neurons corresponding to k class labels. (Adhikari; Naetiladdanon; Sangswang. et al., 2022) The output layer consists of SoftMax operation linked with the feature layer, taking the voltage trajectories input data series, and the probability distribution is generated across the class label of the data sets. The probability distribution is generated across the class label. (Adhikari; Naetiladdanon; Sangswang. et al., 2022) The training and the TempCNN-LSTM model parameters are learned, and the feedforward pass is followed by the backpropagation applied for the cost function minimization.

4. AN APPROACH BASED ON NEURAL NETWORKS AND COMPLEX NETWORKS

The proposed method is a combination of neural networks and complex networks. Through the complex network, the properties are extracted, and the neural networks guide the classification. In case, the graph is represented as $G = (V, E)$, where V indicates the vertices and E shows the edges. $|E|$ and $|V|$ represent the edges and nodes from graph G . The network model is defined as $GN = (V_N, E_N)$. Each edge from graph G is the vertex GN . The weighting vector from every vertex is measured through the relationship evaluation between the edge's geometric position, as shown in the diagram below.

Schematic representation of the complex network graph

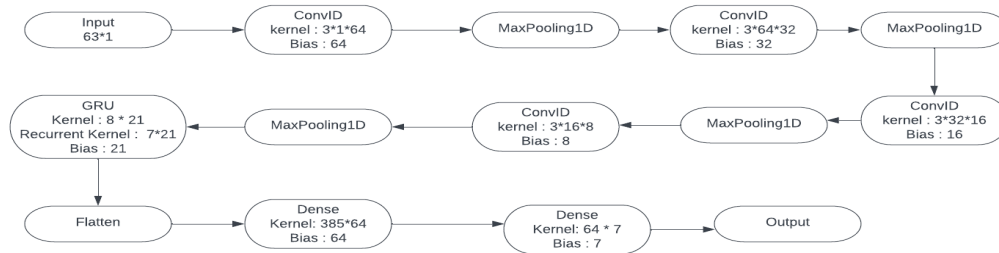


5. ARTIFICIAL JOINT COMMITTEE ON CANCER (AJCC)

Biomarkers of the medical image facilitated the procedure non-invasive and characterized by the heterogeneous tumor. The AJCC automated staging plays a critical role by serving as the auxiliary support system for medical professionals for Non-small cell lung cancer (NSCLC) identification. (Moitra; Rakesh Kr Mandal. et al., Jul 2019) The automation would be independent of Tumor-Node-Metastasis (TNM) staging. In this regard, Machine learning plays a critical role in the automation process implementation. Artificial Neural Networks would be the default choice as the model of Artificial Neural Networks (ANN). Better accuracy is achieved through the Deep Neural Network (DNN). (Moitra; Rakesh Kr Mandal. et al., Jul 2019) DNN structure comprises the INPUT layer holding the extracted features from the target image; the CONVOLUTION layer calculates the outputs of the neurons connected with the input's local regions. The rectified linear units' layer is applied as the function of the element-wise activation function. (Moitra; Rakesh Kr Mandal. et al., Jul 2019) POOLING layer operates down sampling along the Fully Connected and spatial dimensions. DNN model achieves a high accuracy level for categorizing lung cancer but is not supported by sophisticated clinical information. (Moitra; Rakesh Kr Mandal. et al., Jul 2019) NSCLC histology uses deep learning radiomics, achieving an accuracy of 75%. NSCLC deep learning's mutation and classification have better accuracy of 87% under the same study domain.

The study objectives automate the AJCC process staging of NSCLC through the hybrid deep convolutional neural network. The deep learning technique has outperformed the architectures of neural networks and other machine learning techniques on multiple occasions. (Moitra; Rakesh Kr Mandal. et al., Jul 2019) The studies focus on identifying lung cancer as either malignant or benign through a traditional or convolutional neural network. The task image processing executed during the survey is done using MATLAB R2015A and the data mining jobs are performed through WEKA 3.7.2. (Moitra; Rakesh Kr Mandal. et al., Jul 2019) CNN-RNN model is developed and executed using Python 3.5.5 along with TensorFlow as the back end and the Keras API library. The structure of the proposed CNN-RNN model is represented below.

Structure Of the Proposed CNN-RNN model



6. MALWARE DETECTION

Neural networks play a critical role in detecting mobile malware through various practical and theoretical methods. The above system is based on the N-gram algorithm. The software's behavioral characteristics are fetched through static analysis. (Li; Wei; Zhang. et al., 2021) The classification and identification are performed using N-gram algorithms so that the software category is either malignant or benign. The mobile network malicious detecting system identifies the network's malicious activities and protects the malware attacks by the end users. The detection is based on the deep learning attracted by academia. (Li; Wei; Zhang. et al., 2021) USTC-TFC2016 conducts the experiments based on the self-created traffic dataset, and an accuracy of 99.41% is achieved through the classifiers and the final average accuracy. The ideal traffic analysis is desirable without the inspection of packet content or the restrictions on the network environment.

7. CONCLUSION

The experiment's outcome concluded that the proposed CNN-RNN model performed remarkably compared with other machine learning methods. CNN-RNN staging accuracy is approximately 97 +- 2 higher than the nearest competitor random forest. The accuracy during the training phase and the training loss is less than the testing phase loss. The accuracy is steady during the baseline and higher resampling iterations. CNN-RNN standard deviation is on the lower side compared with other algorithms. CNN-RNN's higher accuracy shows the ability to perform while carrying out the multi-class problem accurately. The standard deviation is lower because of the steady accuracy level.

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Arvind Chandrasekaran from Texas, USA. Presently working for PPG Healthcare for the past six years. I have also been pursuing Doctorate in Computer Science (Big Data Analytics) from Colorado Technical University for the past two years, having completed 54 credits; I'm looking to achieve the same by this year.