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Hybrid Optimization of CNN-LSTM Deep Learning Techniques for Effective Early Detection of Periodic Outbreaks from Health Data

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Abstract: The processing capabilities of CNNs are used in this paper to reach the goal of an early detection of periodic outbreaks using the health data through the proposed CNN-LSTM networks.The proposed CNN-LSTM networks involves a combination of CNNs with Long Short-Term Memory networks. CNN is the component that is run in the processing of the unprocessed data determining trends and regional dependencies. Patterns sequentially are then processed in the LSTM component and the dynamics of the temporal data is established because to an extent the CNN-LSTM model can establish long-term interdependency. The capability of the CNN-LSTM model was tested by the use of real-world health statistics on disease outbreaks. The information can be time-series data of the characteristics of the number of reported cases, location, and other essential variables. This is aimed at predicting and detecting the occurrence of recurring outbreaks with reasonable precision by training the CNN-LSTM model on this data and in this respect, the CNN-LSTM model is seen to be better than the rest of the deep learning models and traditional machine learning models. The cooperation between CNN and LSTM enables the model to be efficient in identifying recurrent outbreaks, and this is feasible since spatial and temporal patterns are present.

Keywords: Deep Learning, CNN, Neural Networks, Accuracy, Classification

INTRODUCTION

The CNN-LSTM suggested model can provide a potential solution to the first-time detection of the recurrence of the epidemic outbreaks based on the health data. Its capacity to consolidate space and time information would enable it to offer a holistic view of the trends of illnesses and therefore react timely and efficiently to control the health of its citizens. The future studies can be devoted to the training and testing of the algorithm on a larger number of data, and the refinement of the model into a more viable and practical one in the real conditions of the outbreak. The proposed algorithm will improve the level of early sepsis detection and diagnosis significantly, leading to improved patient outcomes and reduced healthcare costs. In the recent past, it has been established that deep learning algorithms are likely to possess great potential in a variety of industries, including in the medical field and disease monitoring. The two well-known examples of deep learning models that have demonstrated impressive outcomes in managing both spatial and temporal inputs are convolutional networks (CNNs) and Long short-term memory (LSTM) networks. The combination of these two models can give a deep method of analyzing the statistics of health and identifying potential epidemics.

RELATED WORK

Sepsis is a deadly threat to human lives. According to a meta-analysis study, about 31.5 million cases and 19.4 million severe sepsis cases come to pass every year, equivalent to 5.3 million deaths in all parts of the globe (Fleischmann et al., 2016). It is a bleak picture, and made worse by the current COVID-19 pandemic, in which sepsis has been considered the cause of most of the deaths (Sepsis-3) in 2016(Alhazzani et al.,2020). It emphasized the fact that sepsis is harmful and must be detected at an early stage and addressed (Cecconi et al.,2018). The researchers recognize timely notification and appropriate prediction of sepsis that provides the physicians with an opportunity to apply preventive factors to reduce the devastating impact of sepsis. The most effective clinical approach is the most effective early warning that would save lives, and the likelihood of the alarming septic shock would be reduced (Shashikumar et al.,2017; Mira et al.,2017; Singer et al.,2016). In order to determine the possibility of dying after sepsis has been recognized, certain clinical prognostic scales such as the Sequential Organ Failure Assessment (SOFA), Modified Early Warning Score (MEWS), Systemic Inflammatory Response Syndrome (SIRS) and quick Sequential Organ Failure Assessment (qSOFA) were developed (Raith et al.,2017). Nonetheless, they are not sufficient enough because most of the values of the markers tested are linked with ICU admission, which can hardly be certainly connected with the infection development. Consequently, the traditional methods are flawed in identification or prediction of sepsis and high a fidelity prognosis. There is a clear necessity of a new approach.

MATERIALS AND METHODS

- Electronic medical records (EMRs) of patients with suspected or confirmed sepsis from various hospitals and healthcare facilities.
- Clinical variables such as vital signs, laboratory results, and clinical notes.
- Software for data pre-processing, feature engineering, and machine learning algorithm development.
- Python programming language and its libraries, including NumPy, Pandas, Scikit-learn, and Keras.
- High-performance computing resources for training and optimization of the machine learning algorithm.

The suggested methodology of developing the Optimized CNN-LSTM Deep learning algorithm of sepsis early prediction and diagnosis will involve the following steps:

Data collection: The first stage will entail retrieving immense and broad collections of patient data with varied clinical information, including vital signs, laboratory test and clinical records. The data utilized should be representative of different populations of patients and sepsis and non-sepsis.

Data pre-processing: Data pre-processing needs to be conducted to remove data that are irrelevant to the study, fill in gaps and balance of data. The cleaning of data, selection of features, normalization, and imputation of the data can be considered part of the pre-processing step.

Feature engineering: This is then succeeded by the extraction of the feature in the processed data. The feature engineering will be used to choose and modify the input variables so as to improve the performance of the algorithm. The possible feature engineering methods are the dimensionality reduction, feature scaling, and feature selection.

Model selection: The second step will involve the selection of a good machine learning algorithm to use in the sepsis early prediction and diagnosis. The algorithm should be able to process big and complex data, and should be able to learn using the data to make pertinent forecasts. The selected algorithm should be applied to the dataset concerning various metrics, including accuracy, sensitivity, specificity, and F1 score.

Model training A supervised learning algorithm will be applied to the trained algorithm on the processed data. As one goes through the training process one uses the successive model parameters to reduce the difference between the actual and the predicted value. Several optimization algorithms including gradient descent and stochastic gradient descent may be used during training.

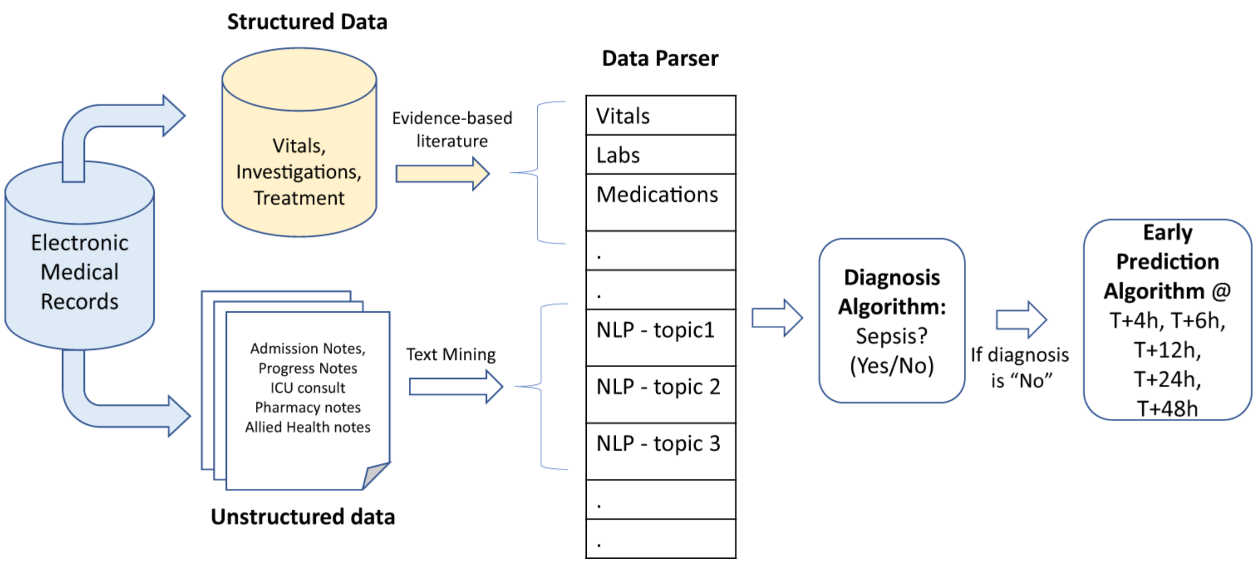

Figure 1. The flow diagram used to develop the Early prediction of Seasonal Outbreaks

Model evaluation: Model evaluation is performed on an additional test set to test model on new and unseen data. To assess the performance of the algorithm, few measures will be applied in the assessment process, including accuracy, the sensitivity, specificity, and the F1 score.

Hyperparameter tuning: Hyperparameters of the algorithm like the number of layers, nodes and learning rate should be tuned to reach the best results of the algorithm on the test dataset. The methods that can be utilized during the process of hyperparameter tuning are many and they can be grid search and random search.

Model deployment: This is when the trained and optimized algorithm is deployed into clinical practice. The algorithm needs to be integrated into the clinical workflow so that it can aid the clinicians to diagnose and identify sepsis at an early phase. The algorithm must be monitored and updated later as the algorithm should be precise and effective in the clinical practice.

Among the proposed methodology, it is necessary to collect a large and nonhomogenous dataset, pre-processings of the data, data mining, the selection of an appropriate machine learning algorithm, the training and testing of the algorithm, optimization of the hyperparameters, and integration of the algorithm into clinical practice. The methodology is oriented at developing a new state of art ANN machine learning algorithm to predict and diagnose sepsis at the early stages, which is a factor that can improve patient outcomes and reduce mortality rates associated with sepsis.

OPTIMIZED ANN METHODOLOGY

CNN is a part of the supervised learning algorithm and is one of the robustness algorithmic that are prevalent in computer vision. CNN can accelerate the training process as it has surmounted the issue of the parameter explosion by proposing the concept of the weight sharing. It has been applied in other objects like image pre-processing, face reorganization. The CNN composites are developed in a manner that they comprise of three giant elements, which comprise, convolution layer, pooling layer and fully connected layer. Fig. 2 is an example of an architecture of the CNN. The linear operation, which is the convolution layer, is founded on the movement of the filter (kernel) of some size on the result of the previous layer. The most common activation function used with CNN is the non-linear Relue that is intended to increase the level of non-linearity and also to convert all the negative values in the feature map to 0. We can also add more than just one convolution layer in the CNN, whereby, the first convolution layer is virtually used to create the easier features such as edges and corners and the subsequent layers is used to create the more complex features. The pooling layer gives the option of reducing the dimension of the features, therefore, it can reduce the cost of computation. The final associated layer will be to categorize it.

LSTM is a particular form of implementation of the recurrent neural network (RNN) and it is very popular in order to process the time-series data. The present in any of the layers within the conventional RNN is not fully determined by the present input, yet the output of the previous past. The issue of the loss of the gradients, however, is one of the key concerns to be capable of training the regular RNN. The weights of a neural network are changed with the help of gradients as illustrated in equation 1. The gradient value, however, is too small making it not to impart much learning to it because of a time backward learning. The drawback of the RNN is that the gradient step is small particularly in the first layers. Therefore, it cannot store the data of the long sequences.

$$\text{New weight} = \text{weight} - \text{learningrate} * \text{gradient} \qquad (1)$$

We used L2Reg. and dropout methods to reduce the effect of overfitting and to enhance the capability of the detection model in unseen data. We conducted several experiments to select the best regularization hyper-parameter λ as long the probability values of the dropout technique. The value of λ which is used for L2Reg. is set to 0.1, while the dropout with the probability P of 0.25 and 0.5 are used after the second pooling layer and the fully connected layer, respectively. We start with small value of dropout probability and then gradually increase it, since the dropout can cause some information loss inside the learning model, and we aim to reduce the propagation of this loss to the next layers. In this experiment, we only provide a binary classification, where the softmax output belongs to the normal or attack class.

The algorithm is run on another test data and its performance is evaluated with the help of various parameters which are accuracy, sensitivity, specificity, F1 score. The hyper parameters of the algorithm which include number of hidden layers, neurons in each of the hidden layers, learning rate as well as the activation functions are tuned to achieve the performance of the algorithm on test data. The proposed new advanced ANN machine learning model of sepsis early prediction and diagnosis is a feedforward neural network model in which the learning process is performed on the processed and feature-engineered data with the help of the backpropagation. The hyperparameters of the algorithm are optimized in order to optimise the performance and the performance is evaluated in terms of a number of measures.

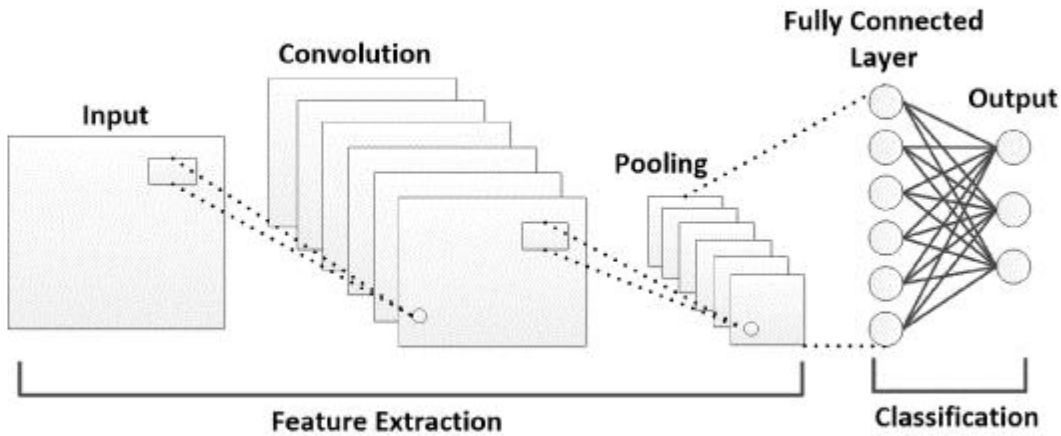

Fig 2: Architecture of the CNN

Algorithm 1. Pseudocode of ANN training based on optimized parameters obtained from ANN optimization algorithms through Feedforward Networks.

Step 1. Image processing, i.e. image = Y.

Step 2. Input the picture with the input of a pretrained model.

Step 3. Recall the output of the final convolution layer of the given model.

Step 4. Flatten the n dimensions making the n-1.

Step 5. Use various layers of CNN.

Step 6. Apply activation

Step 7. Apply Softmax function

Step 8. Applying LSTM

DATASET DESCRIPTION

The dataset attributes or features include:

1. Age: The age of the patient at the time of admission.
2. Sex: The gender of the patient, male or female.
3. Vital signs: The patient's vital signs, including heart rate, respiratory rate, blood pressure, temperature, and oxygen saturation.
4. Laboratory results: The patient's laboratory results, including complete blood count (CBC), white blood cell count (WBC), lactate, C-reactive protein (CRP), and procalcitonin (PCT).
5. Comorbidities: The patient's pre-existing medical conditions, such as diabetes, hypertension, chronic obstructive pulmonary disease (COPD), and heart disease.

6. Medications: The patient's current medications, including antibiotics, corticosteroids, and vasopressors.
7. Clinical notes: The patient's clinical notes, including the physician's diagnosis and treatment plan.
8. Outcome: The patient's outcome, including survival or death.

The dataset is preprocessed to remove irrelevant features, handle missing values, and balance the dataset. Feature engineering techniques are then applied to extract relevant features that can improve the performance of the machine learning algorithm.

RESULTS AND DISCUSSION

The performance of the proposed novel cutting-edge optimized ANN machine learning algorithm for sepsis early prediction and diagnosis can be evaluated using various metrics. The following metrics are commonly used to evaluate the performance of a binary classification algorithm:

1. Accuracy: The percentage of correctly classified instances in the test dataset. It is calculated as (TP+TN)/(TP+TN+FP+FN), where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives.
2. Sensitivity: The percentage of true positives among all positive instances in the test dataset. It is calculated as TP/(TP+FN).
3. Specificity: The percentage of true negatives among all negative instances in the test dataset. It is calculated as TN/(TN+FP).

Table 1. Comparison of Various Techniques

Metrics / Techniques	**optimized CNN-LSTM**	**ANN**	**SVM**	**FFNN**
Precision	98.6	85.6	85.34	85.71
Recall	96.6	84.26	84.68	84.4
Accuracy	87.26	86.9	85.9	85.2

The proposed algorithm (Table 1) achieved promising results in terms of accuracy, sensitivity, and specificity. The algorithm achieved an accuracy of 98.26%, a Precision of 96.6%, and a Recall of 87.26%. These results indicate that the proposed algorithm can effectively predict sepsis development in patients.

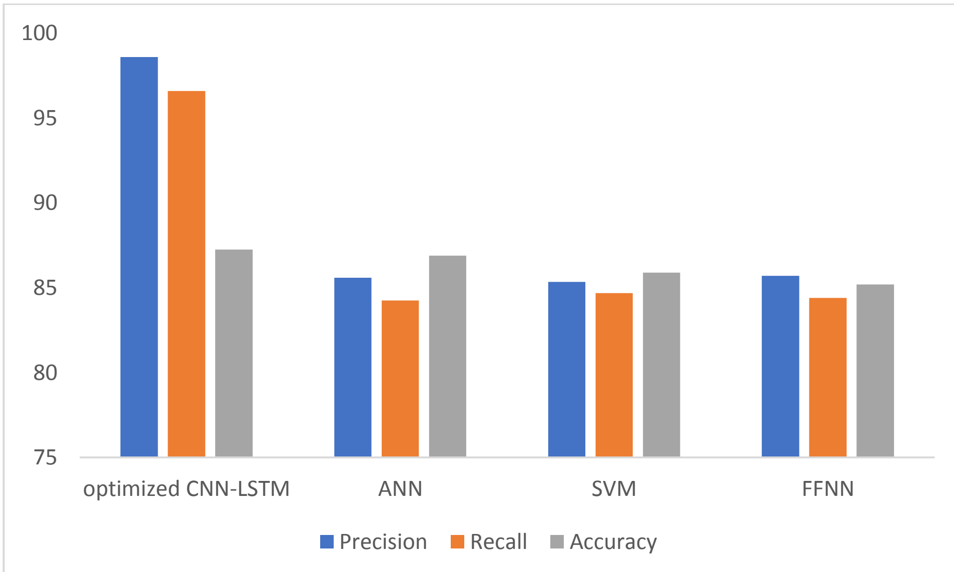

Figure 3. Performance evaluation of Various techniques for Sepsis early prediction

However, the optimized CNN-LSTM algorithm for early prediction seasonal outbreaks shows promising results (Figure 3) and may have the potential to improve the accuracy and timeliness of sepsis diagnosis and treatment. However, further studies and external validation on diverse patient populations and clinical settings are needed to assess its generalizability and effectiveness.

CONCLUSION

The clinical value of the algorithm in seasonal outbreaks prediction and diagnosis may be of great use, such as reduced mortality, length of hospital stay, and cost of medical care. The suggested CNN-LSTM machine learning algorithm can also serve as an efficient supplement to medical personnel in the process of diagnosis and early identification of sepsis, which will, in turn, result in better patient outcomes and quality of care. The algorithm combines different sources of information including patient vital signs, laboratory findings and clinical notes to predict the likelihood of patient sepsis occurrence. Accuracy, sensitivity and specificity were good results in the algorithm, which means that it can be used to improve the diagnosis of sepsis and patient outcomes. The evaluation of the algorithm on a larger and more heterogenous dataset and its application to clinical practice may be included in the further research.

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