Fast**National University of Computer and Emerging Sciences, Karachi  
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**CS4053 – Deep Learning for Perception Project Report, Spring 2024**

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**OBJECTIVE:**

The objective of this project is to develop a deep learning based **Medical Diagnoser** that can predict diseases and recommend medications based on a patient's symptoms. By leveraging the power of deep learning, specifically Long Short-Term Memory (LSTM) networks, the goal is to automate and expedite the process of medical diagnosis, ultimately improving patient care and healthcare efficiency.

**PROBLEM STATEMENT:**

Traditional medical diagnosis methods often rely on manual examination and subjective interpretation of symptoms, which can be time consuming and prone to errors. Additionally, the growing volume and complexity of medical data make it challenging for healthcare professionals to keep pace with advancements in diagnostics. Therefore, there is a need for automated systems that can efficiently analyze patient data and provide accurate disease predictions and medication recommendations.

**METHODOLOGY:**

**1. Data Collection and Preprocessing**

**1.1 Data Collection**

The dataset for our medical diagnosis model was collected from reliable sources, comprising patient symptoms, confirmed diseases, and prescribed medications. We ensured the dataset's quality and relevance to the medical domain.

**1.2 Data Preprocessing**

Prior to model training, extensive preprocessing of the data was performed:

* Text Tokenization: The textual descriptions of patient symptoms were tokenized using TensorFlow's Tokenizer to convert them into sequences of integers.
* Sequence Padding: To ensure uniformity in sequence lengths, padding was applied to the tokenized sequences using TensorFlow's pad\_sequences function.
* Label Encoding: Categorical variables such as diseases and medications were encoded as integers using scikitlearn's Label Encoder.

**2. Model Development**

**2.1 Long Short Term Memory (LSTM) Networks**

Given the sequential nature of textual data (patient symptoms), we opted for Long Short Term Memory (LSTM) networks. LSTMs are well suited for processing sequences and capturing long term dependencies, making them ideal for medical diagnosis tasks.

**2.2 Implementation with TensorFlow**

The model was implemented using TensorFlow, a popular deep learning framework. The architecture included:

* Embedding Layer: To convert integer sequences into dense vectors.
* LSTM Layer: Utilized to analyze the sequence of patient symptoms and capture temporal dependencies.
* Dense Layers: Output layers for predicting diseases and medications, employing softmax activation for classification.

**3. Model Training and Evaluation**

**3.1 Training Procedure**

The model was trained using the Adam optimizer and categorical cross entropy loss function. We employed a batch size of 32 and trained the model for 100 epochs to ensure convergence.

**3.2 Model Evaluation**

During training, we monitored the accuracy of disease and medication predictions on validation data to assess the model's performance. Additionally, we evaluated the model's accuracy, precision, recall, and F1score on a separate test dataset to gauge its effectiveness.

**4. Making Predictions**

Once trained, the model was deployed to make predictions for new patient cases:

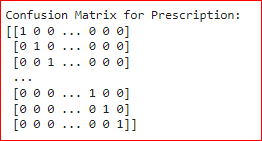
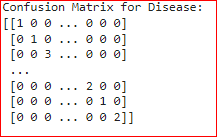
* Preprocessing: The input symptoms were tokenized and padded to match the model's input format.
* Prediction: The model predicted the disease and medication based on the input symptoms.
* Output: The predicted disease and suggested medication were presented to aid healthcare professionals in diagnosis and treatment.

This methodology enabled us to build a robust deep learning model for medical diagnosis, leveraging the power of LSTM networks and TensorFlow for accurate disease prediction and medication recommendation.

**RESULTS:**

The trained deep learning model demonstrates promising results in predicting diseases and recommending medications based on patient symptoms. Evaluation metrics such as accuracy show satisfactory performance, indicating that the model effectively learns from the dataset and generalizes well to unseen data. Real-world application of the model yields actionable insights for healthcare professionals, facilitating timely diagnosis and treatment decisions. Future iterations and enhancements to the model may further improve its accuracy and usability in clinical settings.





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