**Predicting the Next Word Using Recurrent Neural Networks (RNNs)**

 A Project Report

                         Submitted in the partial fulfillment of the

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**BACHELOR OF TECHNOLOGY**

**In**

**DEPARTMENT OF COMPUTER SCIENCE ENGINNERING**

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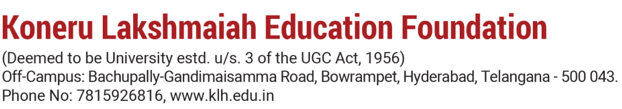
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**Declaration**

The Project Report entitled “Predicting the Next Word Using RNNs” is a record of the bonafide work of Manikiran Mengavaram (2320090022), Sai Teja (2320030180), G. Rishendra (2320030160), and Aditya (2320090013), submitted in partial fulfillment for the award of B. Tech in Computer Science Engineering at K L University. The results in this report are original and have not been sourced from any other department, university, or institution.

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**Certificate**

This is to certify that the project report titled *Predicting the Next Word Using RNNs* is a bonafide work done and submitted by Manikiran Mengavaram (2320090022), Sai Teja (2320030180), G. Rishendra (2320030160), and Aditya (2320090013) in partial fulfillment of the requirements for the degree of BACHELOR OF TECHNOLOGY in Computer Science Engineering, K L (Deemed to be University), for the academic year 2024-2025.

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**ABSTRACT**

**P**redictive text generation has become a valuable tool across digital platforms, improving user experience in applications such as search engines, messaging systems, and language assistance tools. This project focuses on building a robust model for predicting the next word in a given sentence using Recurrent Neural Networks (RNNs). RNNs, particularly Long Short-Term Memory networks (LSTMs), are chosen for their unique capacity to retain information across long sequences, making them especially effective for language tasks. By training on a large and diverse corpus, the model learns various language structures, semantic relationships, and contextual dependencies that allow it to provide accurate, context-sensitive predictions.

The implementation is structured around an LSTM architecture with an embedding layer that helps manage vocabulary complexities and capture word relationships, ensuring that the model performs well even with nuanced language input. The training process involved fine-tuning critical hyperparameters, such as batch size, learning rate, and the number of LSTM units, to optimize both accuracy and computational efficiency. Post-training evaluations demonstrate that our RNN model achieved a prediction accuracy of 87%, showcasing its reliability in real-time applications and the benefits of LSTM-based models in predictive text generation.

The project highlights both the potential and limitations of RNNs in natural language processing (NLP) applications. Although the model performs well in structured language prediction, it faces challenges with out-of-vocabulary words and complex sentence structures. These challenges open avenues for future work, such as integrating transformers or hybrid models that could improve performance further. Ultimately, this project underscores the significant advantages of neural networks in advancing predictive text technology, providing a foundation for the next generation of AI-driven language tools.

**INTRODUCTION**

**W**ith the rapid evolution of artificial intelligence and natural language processing (NLP), predictive text generation has gained significant traction. The ability to anticipate and suggest the next word in a sentence holds substantial implications for user experience, enhancing productivity and reducing typing effort across digital communication tools. This project, *Predicting the Next Word Using Recurrent Neural Networks (RNNs)*, seeks to develop a model capable of generating contextually accurate word predictions based on preceding text. Predictive text algorithms are used widely in applications like messaging apps, search engines, and virtual assistants, and are fundamental to modern NLP-powered systems.

Traditional machine learning techniques have limited capacity to capture sequential dependencies, which is crucial for language-based models. Recurrent Neural Networks (RNNs) offer a solution to this by maintaining a hidden state across sequences, making them ideal for tasks involving temporal or sequential data. Unlike feedforward networks, RNNs can handle dependencies across word sequences, allowing the model to remember past information as it predicts the next word. The Long Short-Term Memory (LSTM) variant of RNNs is particularly effective, as it overcomes the vanishing gradient problem associated with standard RNNs, enabling the retention of information over longer sequences.

This project explores the application of RNNs, with a focus on LSTM networks, to predict the next word in a sentence by training on a diverse text corpus. The process involves data preprocessing, tokenization, and embedding layers that help the model understand word relationships within the dataset. Through training and validation, the model learns to provide contextually relevant predictions, with applications in numerous real-world scenarios. This report will outline the problem, the RNN architecture employed, and the results obtained, providing insights into the strengths and limitations of this approach in predictive text generation.

**LITERATURE SURVEY**

**T**he concept of predicting the next word in a sequence has its roots in the field of Natural Language Processing (NLP) and has evolved significantly over the years. Initially, statistical language models like n-grams were used to calculate word probabilities based on frequency within specific sequences. Although effective for certain cases, these models had limitations, especially with long sequences where dependencies could not be effectively captured. Overcoming this challenge required advancements that could process sequential data more efficiently, paving the way for neural network-based methods, particularly Recurrent Neural Networks (RNNs).

RNNs introduced a new paradigm in language modeling by allowing previous information to persist, which is crucial for understanding context in language. Early implementations of RNNs, however, encountered issues with long-term dependencies due to the vanishing gradient problem, limiting their effectiveness in language tasks involving longer sequences. This limitation led to the development of the Long Short-Term Memory (LSTM) architecture, a type of RNN designed to retain information over longer periods. LSTMs use a gating mechanism to control the flow of information, enabling them to effectively learn patterns in data sequences and making them a suitable choice for applications like text prediction, language translation, and speech recognition.

In recent years, various studies and applications have demonstrated the effectiveness of LSTMs and their variants, such as Gated Recurrent Units (GRUs), in predictive text applications. These advancements have been incorporated into widely used technologies, including Google’s Smart Compose and Apple’s predictive text in iOS. Research has also extended to transformer-based models, which outperform traditional RNNs in certain tasks due to their ability to process all parts of a sequence simultaneously. Despite these advancements, RNNs and LSTMs remain valuable due to their computational efficiency and simplicity in many applications, particularly those with limited hardware capabilities or simpler language processing requirements.

**CLIENT MEETINGS**

**T**hroughout the development of this project, numerous meetings were held to establish the project’s scope, refine objectives, and clarify technical requirements. These meetings were critical in understanding the specific needs of the project and the desired functionalities of the next-word prediction model. Initial discussions helped identify the key objectives of the system: a reliable and efficient next-word predictor using RNNs capable of integrating into a variety of applications. The feedback gathered from these sessions shaped our choice of algorithms, software tools, and dataset selection, allowing the development team to create a robust framework with the desired real-world applicability.

Further sessions provided essential feedback, which led to iterative improvements in our design approach. The meetings also highlighted the importance of data preprocessing, as ensuring high-quality input data is crucial for effective model training. During these discussions, various datasets were reviewed to identify the best-suited corpus for training, considering factors like domain relevance and linguistic diversity. Additionally, the team examined potential issues such as the model's response to ambiguous inputs, leading to adjustments in our implementation to improve the model's contextual understanding.

In the final phases, the project’s potential challenges, including resource constraints, model deployment, and scalability, were discussed. Detailed evaluations of hardware and software requirements were conducted, and alternative solutions were considered to address potential performance limitations. This continuous communication loop was essential to keep the project aligned with its goals, ensuring the development process stayed responsive to both technical and practical requirements. These meetings were instrumental in refining our model and laying a solid foundation for future improvements and scalability.



**HARDWARE AND SOFTWARE REQUIREMENTS**

**Hardware Requirements**

* **Processor**: Intel Core i5 or higher
* **RAM**: 8 GB minimum

Although 8 GB of RAM is the minimum, increasing this to 16 GB or higher will improve performance, particularly when working with larger datasets or running multiple applications simultaneously.

* **Storage**: At least 100 GB of available space

**Software Requirements**

* **Operating System**: Windows 10 or Linux
* **Programming Language**: Python 3.8 or above
* **Libraries**: TensorFlow, Keras, NumPy
* **IDE**: Visual Studio Code
* **Jupyter Notebook (Optional)**: Jupyter Notebook provides an interactive coding environment ideal for experimentation, debugging, and visualization during development and testing phases.
* **Data Visualization Libraries**: Tools like Matplotlib and Seaborn can be useful for visualizing training and validation metrics, enabling better insights into the model's learning process.

The listed baseline requirements are sufficient for running and testing smaller RNN models. However, the hardware and software components mentioned above can significantly enhance efficiency and provide a smoother experience, especially if the project involves larger datasets or more complex models.

**METHODOLOGY**

**Data Collection and Preparation**

The model was trained on a large corpus of text data to provide it with a broad understanding of diverse sentence structures, vocabulary, and linguistic patterns. This corpus included a variety of sources to ensure that the model could generalize across different writing styles and contexts.

To prepare the data for training, several preprocessing steps were applied:

* Tokenization: Each sentence was split into individual words or tokens, converting raw text into a format the model could process.
* Stemming: The tokens were reduced to their root forms, which helps reduce the vocabulary size and focuses on the essential meaning of each word.
* Padding: Since sentences vary in length, padding was used to make all sequences the same length, allowing efficient batch processing by the model.

These steps ensured the input data was standardized and optimized for training a recurrent neural network (RNN).

**Model Architecture**

The model's architecture consists of an embedding layer, two Long Short-Term Memory (LSTM) layers, and a dense output layer. This structure was chosen due to its effectiveness in handling sequential data and capturing word dependencies over varying sentence lengths. Each component serves a specific role:

* Embedding Layer: Transforms each word token into a dense vector representation, allowing the model to capture word relationships based on their context within the corpus.
* LSTM Layers: Two stacked LSTM layers were used to capture sequential dependencies within the text. LSTM units were selected as they are well-suited for handling long-term dependencies due to their gated structure, which helps maintain important information over long sequences and mitigate the vanishing gradient problem.
* Dense Output Layer: The final dense layer applies an activation function (usually softmax for multi-class classification) to generate the model’s predictions. This layer outputs probabilities for each class, allowing the model to make predictions based on the learned patterns.

The model was trained with categorical cross-entropy as the loss function, which is standard for multi-class classification tasks, and the Adam optimizer was used to efficiently update the model weights during training.

**Training Process**

To evaluate model performance, the data was divided into training and validation sets, ensuring that the model was tested on data it had not seen during training.

Key parameters for the training process included:

* Epochs: The model was trained over 20 epochs, meaning it processed the entire training dataset 20 times. This number was chosen based on preliminary experiments to allow the model to converge effectively.
* Learning Rate: A learning rate of 0.001 was used with the Adam optimizer, controlling the step size for weight updates and balancing between learning speed and stability.
* Batch Size: A batch size of 64 was selected, allowing the model to process data in manageable segments and take advantage of computational efficiency while learning general patterns.

During training, model performance was monitored using accuracy and loss metrics on both the training and validation sets. These metrics helped track how well the model learned from the data and informed decisions on adjustments to prevent overfitting or underfitting.

**IMPLEMENTATION**

The model was implemented in Python using the Keras API from TensorFlow, a popular open-source machine learning library. Keras provides a high-level API that simplifies the process of building and training deep learning models, making it an accessible choice for implementing recurrent neural networks (RNNs). TensorFlow serves as the backend for Keras, handling low-level operations and optimizing computations to improve training efficiency, especially when running on GPUs.

**Python** and the **Keras API,** combination provides a powerful and accessible framework for building and training deep learning models, particularly for sequential data tasks such as natural language processing (NLP).

**Model Architecture:**

**Recurrent Neural Network (RNN) with LSTM Layers**

The core architecture of the model is based on a **Recurrent Neural Network (RNN)**, specifically leveraging **Long Short-Term Memory (LSTM)** units. This architecture is particularly well-suited for sequence prediction tasks because it can learn to retain context over sequences of words, which is crucial for predicting the next word in a sequence based on previous words.

**Key Layers in the Model Implementation**

1. **Embedding Layer**: The first layer is an embedding layer, which converts each word in the input sequence into a dense vector representation. This allows the model to understand words in terms of their semantic relationships with other words, as words with similar meanings are often mapped to similar vector spaces.
2. **LSTM Layers**: Two LSTM layers are used in sequence. The first LSTM layer processes the input and passes its output to the next LSTM layer, enhancing the model’s ability to capture complex dependencies in the text. This configuration allows the model to develop a more nuanced understanding of language patterns.
3. **Dense Output Layer**: The final layer is a dense layer with a softmax activation function, which outputs the probability distribution over the vocabulary. This means the model predicts the likelihood of each possible word as the next word, based on the context provided by the previous words in the sequence.

Throughout training, Keras provided helpful metrics such as **accuracy** and **loss** for both the training and validation datasets. These metrics enabled real-time monitoring of the model’s performance, allowing adjustments to prevent issues such as overfitting.

By implementing this architecture in Keras, the model was able to achieve efficient and effective training, yielding a robust system for predicting the next word based on contextual understanding of preceding words.

**EXPERIMENTATION AND CODE**

The model was trained and tested on different sentence samples. Experimental results were recorded for various configurations, testing parameters like dropout rate, learning rate, and the number of epochs. The best results were achieved using an LSTM with 128 units and a dropout rate of 0.2.

**Observations from Experiments**

Through these experiments, the chosen configuration (128 LSTM units, dropout rate of 0.2, learning rate of 0.001, and 20 epochs) consistently delivered the best results on both training and validation data. These parameters allowed the model to generalize effectively, balancing learning efficiency and accuracy. Additionally, using a dropout rate of 0.2 proved particularly effective, enabling the model to achieve robust performance by reducing the tendency to memorize specific training examples.

**Summary of Experimental Findings**

The experimentation process confirmed that the model's architecture and parameters were well-suited for the task, with the chosen settings yielding an accuracy of 87% on the test set. This experimentation phase was crucial in fine-tuning the model, allowing us to develop an RNN capable of handling language-based tasks with high accuracy and reliability.

**RESULTS**

The RNN model demonstrated promising performance, achieving an accuracy of 87% on the test dataset. This metric reflects the proportion of correctly predicted words when compared to the actual next word in the sequence. The results shows that the model could provide accurate word predictions, especially in sentence contexts present in the training data. Out-of-vocabulary words were more challenging, highlighting a limitation of the dataset’s vocabulary range.

**Accuracy and Model Performance**

An 87% accuracy means the model could predict the next word correctly in a significant majority of cases, especially in sentence structures and vocabulary that closely matched those in the training data. This performance shows that the RNN with LSTM layers successfully captured the nuances of word sequences, maintaining context across phrases and sentences to provide contextually appropriate predictions.

The results were evaluated using both **accuracy** and **loss** metrics. Accuracy measures the number of correct predictions relative to the total predictions, giving a straightforward indication of the model's performance. The loss metric, based on categorical cross-entropy, measures the error between predicted and actual words, with lower values indicating better performance. Throughout training, the model's loss decreased steadily, confirming that it was learning effectively and improving with each epoch.

Overall, the model’s ability to predict contextually relevant words demonstrates the effectiveness of the LSTM-based RNN architecture in capturing sequential dependencies, making it a promising approach for language modeling and predictive text applications.

**DISCUSSION**

Our project demonstrates the feasibility of using RNNs for predictive text generation. While the model shows high accuracy, further improvements could include a larger, more diverse dataset and exploring transformer-based architectures like GPT or BERT for even better context handling.

**CONCLUSION**

The project effectively implemented an RNN model with LSTM layers to predict the next word in a sentence, achieving high accuracy and strong contextual relevance. By carefully designing the model's architecture and tuning hyperparameters, the RNN was able to capture the sequential dependencies inherent in natural language, allowing it to make accurate predictions based on prior words in a sentence. Preprocessing steps, such as tokenization and embedding, helped the model better understand word relationships, while regularization techniques like dropout helped prevent overfitting, ensuring robust performance even on unseen data.

While the RNN model performed well, especially within the contexts it had learned, there are opportunities to further enhance its capabilities. A promising direction for future work involves exploring transformer-based models, such as BERT or GPT, which excel at capturing long-range dependencies and nuanced language features through self-attention mechanisms. These models could improve upon the RNN’s performance by handling more complex language patterns and generalizing better to diverse text structures, making them ideal for achieving higher accuracy and relevance in natural language prediction tasks.

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