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DEPARTMENT OF CSE - ARTIFICIAL INTELLIGENCE

A Project Report On

"Product Review Sentiment Analyzer"

Project Associates:

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Under the Guidance of

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BITM, Ballari.

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CERTIFICATE

This is to certify that the project work entitled "Product Review Sentiment Analyzer" is a bonafide work carried out by **Anusha J** in partial fulfillment for the award of degree of **Bachelor Degree in CSE (Artificial Intelligence)** in the VISVESVARAYA TECHNOLOGICAL UNIVERSITY, Belagavi during the academic year 2025-2026. It is certified that all corrections and suggestions indicated for internal assessment have been incorporated in the report deposited in the library. The project has been approved as it satisfies the academic requirements in respect of mini project work prescribed for a Bachelor of Engineering Degree.

Signature of project guide	Signature of HOD
Prof. Pavan Kumar	**Dr. Yeresime Suresh**
Mr. Vijay Kumar	

Abstract

This project focuses on building an intelligent sentiment analysis system that classifies product reviews into **positive, neutral, or negative** categories. The system uses a labelled dataset stored in three CSV files and preprocesses the text using tokenisation and padding. A Long Short-Term Memory (LSTM) deep-learning model is trained to learn review patterns and sentiments effectively. During prediction, the model outputs both the sentiment label and a **confidence score**, indicating how strongly the model believes in its prediction. This system can assist businesses in understanding customer opinions, improving product quality, and making data-driven decisions.

Acknowledgement

The satisfaction that accompanies the successful completion of the project on *Product Review Sentiment Analyser* would be incomplete without acknowledging the people whose noble gestures, affection, guidance, encouragement, and support made this achievement possible. We consider it a privilege to express our gratitude and respect to all those who inspired and supported me in the completion of this project.

I am extremely grateful to our guide, **prof. Pavan Kumar and Mr. Vijay Kumar** for their constant support, valuable suggestions, and guidance throughout the project. Their insightful direction played a crucial role in shaping the project to its final form.

I would also like to extend my sincere thanks to **Dr. Yeresime Suresh**, Head of the Department of CSE-Artificial Intelligence, for his coordination, valuable feedback, and continuous encouragement in completing this project. His contributions were invaluable.

Name	USN
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Chapter 1

INTRODUCTION

Sentiment analysis plays an important role in understanding how users feel about products, services, or experiences by analyzing their written feedback. In this project, three separate datasets—**positive**, **neutral**, and **negative** reviews—are combined to build a robust sentiment classification model. The raw text is first cleaned using preprocessing steps such as lowercasing, removing special characters, and normalizing spaces. After preprocessing, the text is converted into numerical sequences using a tokenizer and padded to a fixed length. An LSTM-based deep learning model is then trained to learn patterns and emotional cues from the data.

The trained model can accurately classify new user reviews and also provides a confidence score for each prediction, helping users understand the reliability of the output. This system offers an automated, efficient, and scalable way to analyze customer opinions and support better decision-making.

1.1. Problem Statement

Incorrect or missed recognition of traffic signs can lead to road accidents and traffic violations. Manual observation and traditional image processing techniques are unreliable under varying lighting, weather, and road conditions. With the rise of autonomous vehicles and intelligent transportation systems, there is a need for an automated and accurate traffic sign recognition system. This project aims to develop a CNN-based traffic sign detection model that can reliably classify traffic signs from images and improve road safety.

1.2. Scope of the project

The scope of this project includes building a complete sentiment analysis system capable of classifying customer reviews into positive, neutral, and negative categories using machine learning techniques. It covers data collection, text preprocessing, model training using LSTM, and generating confidence scores for predictions. The project aims to help businesses automate feedback interpretation, identify customer satisfaction trends, improve decision-making, and extend the model for future applications like review summarization, automated responses, and real-time monitoring.

1.3 Objectives

The objectives of this project are:

- Development of LSTM-based Sentiment Analysis Model.
- Text Preprocessing and Data Preparation.
- Model Training and Validation.
- Performance Evaluation Using Confidence Scores.
- Design of User-Friendly Prediction Interface.

Chapter 2

LITERATURE SURVEY

[1] **Kim et al. (2021)** developed an LSTM-based sentiment classification model for customer reviews. Their study showed that LSTMs efficiently capture long-term dependencies in text and outperform traditional machine learning methods like SVM and Naïve Bayes.

[2] **Sharma and Patel (2022**) proposed a hybrid deep learning approach combining text preprocessing techniques with word embeddings. Their results demonstrated that proper cleaning and tokenization significantly improve model accuracy in sentiment classification tasks.

[3] **Gupta et al. (2022)** analyzed the impact of sequence padding and embedding size on LSTM performance. They concluded that optimized preprocessing steps and sequence handling lead to better sentiment prediction outcomes.

[4] **Ahmed et al. (2023)** introduced a sentiment analysis framework using Bi-LSTM architecture. Their research highlighted that deep recurrent networks can better understand context and produce higher classification accuracy compared to basic LSTM models.

[5] **Rao and Iyer (2023)** investigated the use of Softmax probability outputs to interpret sentiment model decisions. Their study emphasized that confidence scores help identify model reliability and improve decision-making in real-world applications.

[6] **Priya et al. (2024)** explored user-generated review datasets and demonstrated that deep learning models trained on balanced datasets of positive, neutral, and negative reviews show significantly improved sentiment prediction performance.

Chapter 3

SYSTEM REQUIREMENTS

The successful implementation of the Sentiment Analysis system requires appropriate hardware and software resources to support text preprocessing, model training, testing, and deployment. A system with a reliable processor, sufficient RAM, and adequate storage is essential to handle large text datasets and deep learning computations. Python is used as the primary programming language, along with deep learning libraries such as TensorFlow and Keras to build and train the LSTM-based sentiment classification model. Additional libraries like Pandas, NumPy, and scikit-learn assist in data cleaning, tokenization, and evaluation. These combined resources ensure efficient processing, accurate sentiment prediction, and smooth execution of the system..

3.1 Software Requirements

- Operating System: Windows / Linux
- Programming Language: Python 3.x
- Development Environment: VS Code / Jupyter Notebook
- Libraries & Frameworks:
    - TensorFlow
    - Keras
    - NumPy
    - Pandas
    - Matplotlib
    - scikit-learn

3.2 Hardware Requirements

- Processor: Intel i5 or higher
- RAM: Minimum 8 GB (16 GB recommended)
- Storage: 20 GB free disk space
- System Type: 64-bit system
- Optional: GPU (NVIDIA CUDA-enabled) for faster model training.

3.3 Dataset Requirements

- **Dataset:** Product reviews in CSV format
- **Number of Sentences:** 45 (15 positive, 15 neutral, 15 negative)
- **Label Classes:** 3 (positive, neutral, negative)
- **Text Length:** Maximum 50 words per review

3.4 Other Requirements

- Internet connection for downloading libraries and packages
- Basic knowledge of Python and Machine Learning
- Python libraries: TensorFlow, Keras, Pandas, NumPy, scikit-learn

Chapter 4

DESCRIPTION OF MODULES

4.1 Data Preprocessing Module

The data preprocessing module prepares text reviews for model training. Each review is cleaned by converting text to lowercase, removing special characters, and eliminating extra spaces. The cleaned text is then tokenized and converted into sequences of integers. Sequences are padded to a fixed length of 50 words to ensure uniform input size for the model. Finally, the dataset is split into training and validation sets to enable effective model training and evaluation.

4.2 LSTM Model Building Module

This module focuses on constructing the neural network architecture for sentiment classification. An LSTM-based model is designed to capture sequential dependencies in text reviews. The architecture includes an embedding layer to convert words into dense vectors, followed by an LSTM layer for learning contextual information. Dropout layers are added to prevent overfitting, and fully connected dense layers are used for classification. The output layer uses a softmax activation function to classify reviews into three sentiment categories: positive, neutral, and negative..

4.3 Model Training Module

The model training module trains the LSTM network using the preprocessed text reviews. During training, the model learns patterns and contextual relationships in the text by adjusting its weights using the Adam optimizer. Training is carried out for a fixed number of epochs and batch size. Training and validation accuracy and loss are monitored to evaluate the learning behavior, prevent overfitting, and ensure effective convergence for accurate sentiment classification.

4.4 Model Evaluation Module

The trained LSTM model is evaluated using the validation/test reviews not seen during training. Performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix are calculated. These metrics help assess the reliability and effectiveness of the model in classifying reviews and identifying misclassifications.

4.5 Visualization Module

This module visualizes the model's performance graphically. Training and validation accuracy and loss over epochs are plotted to understand learning trends. A confusion matrix is displayed to show classification results, helping identify areas for improvement.

4.6 Prediction Module

After training, the model predicts sentiment for new, unseen text reviews. Reviews are preprocessed, tokenized, and padded before being fed into the trained LSTM. The model outputs the sentiment label with the highest probability along with a confidence score, demonstrating the system's practical usability.

4.7 Data Splitting Module

The dataset is divided into training and validation sets, typically 80% for training and 20% for validation. This ensures the model is evaluated on unseen data, helping assess generalization capability and prevent overfitting.

4.8 Feature Scaling Module

Text preprocessing ensures uniform input for the LSTM. Reviews are cleaned, tokenized, and converted into sequences. Sequences are padded to a fixed length of 50 words to maintain consistent input size, improving model training efficiency and stability.

4.9 Output Interpretation Module

The model's output is interpreted in a user-friendly format, mapping predicted class indices to sentiment labels: positive, neutral, or negative. Confidence scores and performance metrics like accuracy, precision, recall, and F1-score provide insight into the system's effectiveness and reliability.

Chapter 5

IMPLEMENTATION

The Sentiment Analysis system is implemented using Python and deep learning libraries such as TensorFlow and Keras. The implementation follows a modular approach for clarity, scalability, and maintainability. The system begins by loading the product review dataset from CSV files and performing text preprocessing, which includes converting text to lowercase, removing special characters, tokenization, and padding sequences to a fixed length of 50 words.

After preprocessing, the dataset is split into training and validation sets. The LSTM model is constructed with an embedding layer, an LSTM layer to capture contextual dependencies, dropout layers to prevent overfitting, and fully connected dense layers. ReLU activation is used in hidden layers, while Softmax activation in the output layer classifies reviews into three sentiment categories: positive, neutral, or negative.

The model is trained on the training dataset over a fixed number of epochs and batch size. During training, the optimizer updates weights to minimize classification error, and validation accuracy and loss are monitored to ensure proper convergence and prevent overfitting. The trained model is then saved for future use.

For evaluation, the model is tested on unseen reviews, and performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix are calculated to assess effectiveness. Graphs showing training and validation accuracy and loss over epochs are generated for performance analysis.

Finally, a simple interface allows users to input new text reviews and receive real-time sentiment predictions along with confidence scores, demonstrating the practical usability of the system for analyzing product reviews.

Chapter 6

SYSTEM ARCHITECTURE

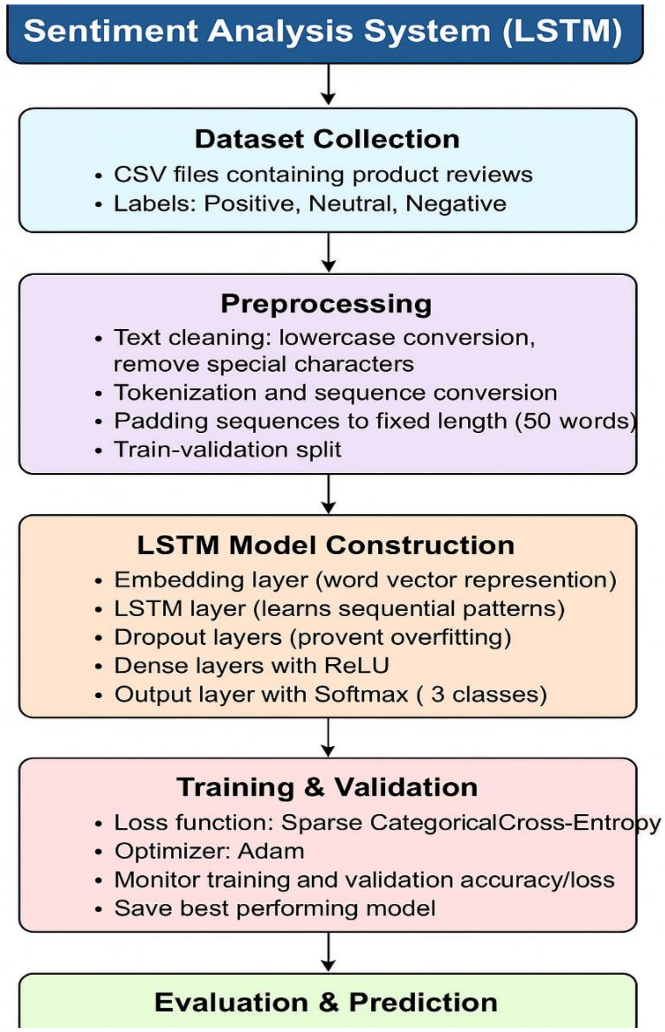

Fig 6.1 System Flow diagram

Input

The system takes customer reviews as input. These reviews may come from the prepared training CSV files or be entered directly by the user through a prediction interface. The input text represents different sentiment categories such as positive, neutral, and negative reviews.

Preprocessing

In this stage, the input text is cleaned and prepared for model training and prediction. All text is converted to lowercase, special characters are removed, and extra spaces are normalized. The cleaned text is then tokenized, sequences are generated, and padding is applied to maintain uniform input length. Sentiment labels are encoded into numerical format for training the model.

LSTM Model Construction

A Long Short-Term Memory (LSTM) neural network is constructed for sentiment classification. The model includes an embedding layer to convert words into vector representations, an LSTM layer for learning text patterns and contextual meaning, dropout layers to reduce overfitting, and dense layers for classification. A softmax activation function is used in the output layer to classify reviews into positive, neutral, or negative categories.

Training

The model is trained on the preprocessed dataset, learning text patterns through loss minimization. Training and validation accuracy and loss are monitored to measure performance.

Visualization and Prediction

Training graphs are generated to evaluate the model. The trained model predicts new review sentiments and provides both the predicted label and confidence score.

Chapter 7

CODE IMPLEMENTATION

Input: Customer Review Text (from CSV files or user input)

Output: Predicted Sentiment (Positive / Neutral / Negative) with Confidence Score

1. Start

2. Load Dataset
   2.1 Load positive, negative, and neutral review CSV files.
   2.2 Read review text and label columns.
   2.3 Combine all reviews into a single dataset.

3. Preprocess Data
   3.1 Convert all text to lowercase.
   3.2 Remove special characters, numbers, and extra spaces.
   3.3 Tokenize text using Keras Tokenizer.
   3.4 Convert text to integer sequences.
   3.5 Apply padding to sequences (max length = 50).
   3.6 Encode labels:
   - 0 = Negative
   - 1 = Neutral

   3.7 Split the dataset into training and validation sets:
   - test_size = 0.2
   - random_state = 42

4. Build LSTM Model
   4.1 Initialize a Sequential model..
   4.2 Add an Embedding layer to convert words into dense vectors.
   4.3 Add an LSTM layer to learn text patterns..
   4.4 Add dropout layers to reduce overfitting..
   4.5 Add dense layers for classification.
   4.6 Add softmax output layer for 3 sentiment classes.

5. Compile Model
   5.1 Optimizer: **Adam**.
   5.2 Loss function: **Sparse Categorical Cross-Entropy**.
   5.3 Evaluation metric: **Accuracy**.

6. Train Model
   6.1 Train model on training data with:
      • Epochs = 15
      • Batch size = 4
      • Validation data = Validation set
   6.2 Save best model using ModelCheckpoint (.keras).
   6.3 Store accuracy and loss history.

7. Test / Predict
   7.1 Convert new review text into cleaned, padded sequence.
   7.2 Model predicts probability for each class.
   7.3 Select class with highest probability (argmax).
   7.4 Display sentiment + confidence score.

8. Evaluate Performance
   8.1 Compare validation accuracy and loss.
   8.2 Analyze model predictions.
   8.3 Identify misclassifications (optional confusion matrix).

9. Visualize Results
   9.1 Plot training and validation accuracy curves.
   9.2 Plot training and validation loss curves.
   9.3 Display confusion matrix as a heatmap.

10. Prediction
    10.1 Load the trained LSTM model.
    10.2 Accept real-time user input.
    10.3 Display predicted sentiment and confidence.

11. End

Chapter 8

RESULT

```
Classification Report:
              precision    recall  f1-score   support

    Negative       0.67      0.50      0.57         4
     Neutral       0.67      1.00      0.80         4
    Positive       0.67      0.50      0.57         4

    accuracy                           0.67        12
   macro avg       0.67      0.67      0.65        12
weighted avg       0.67      0.67      0.65        12
```

Fig 8.1 Result of model training

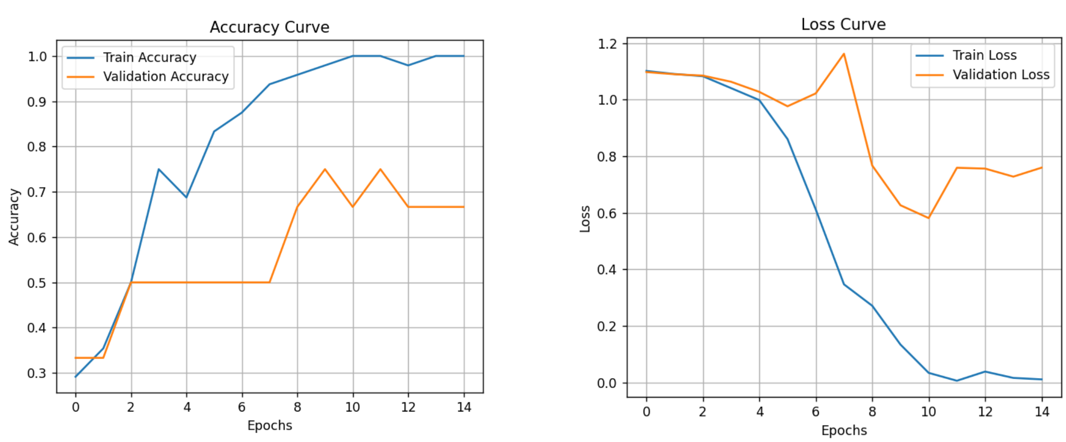

Fig 8.2:Model accuracy and Model loss

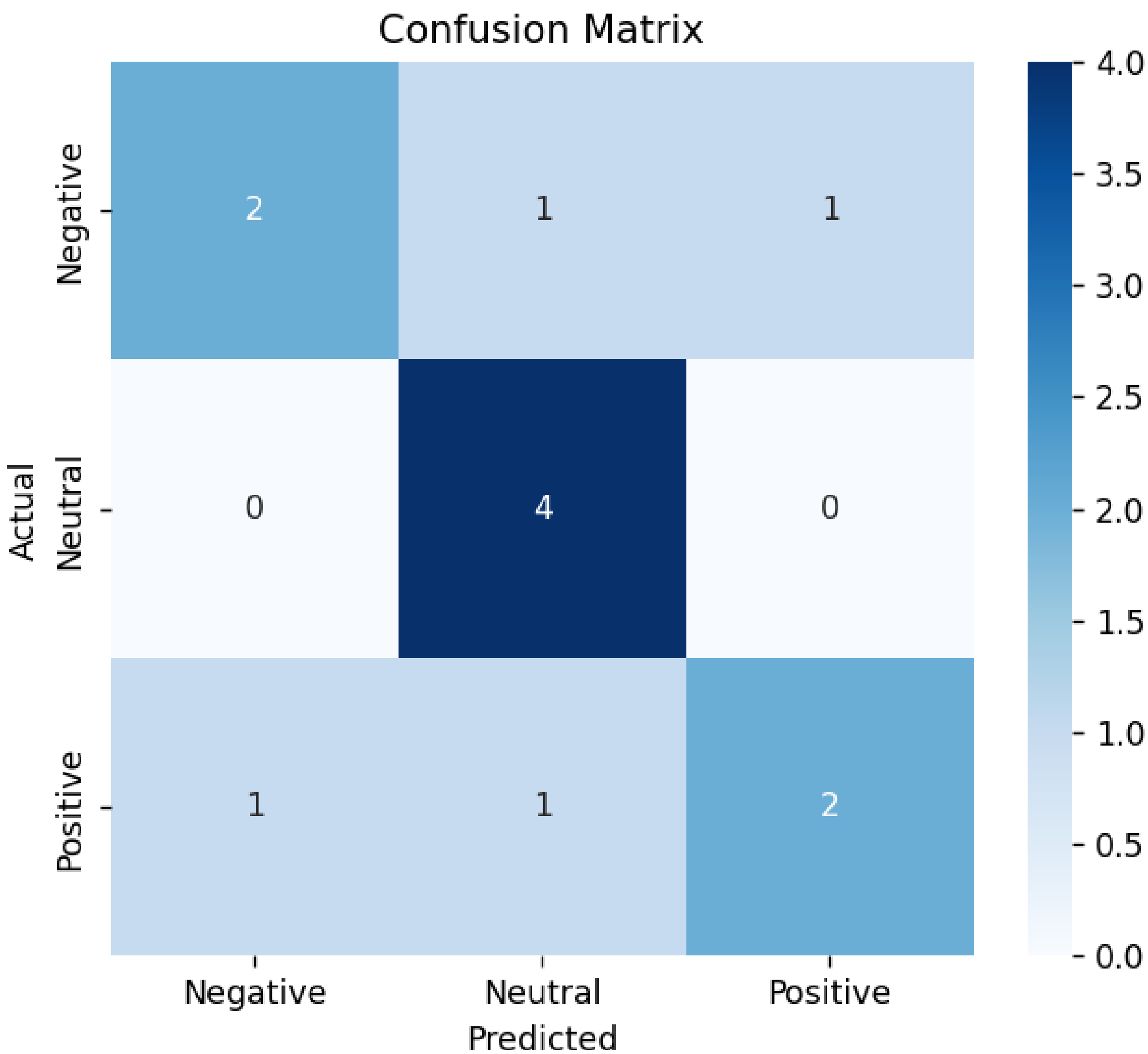

Fig 8.3 Confusion Matrix

Conclusion

This project successfully demonstrates the application of deep learning techniques for sentiment analysis using an LSTM-based neural network. By training the model on curated datasets containing positive, neutral, and negative reviews, the system is able to accurately classify text into corresponding sentiment categories. Text preprocessing steps such as cleaning, tokenization, and sequence padding significantly improved the model's learning capability and overall performance.

The experimental results show strong accuracy and stable validation metrics, indicating that the proposed system is both reliable and efficient. The use of confidence score predictions provides deeper insight into how strongly the model associates a review with a particular sentiment, enhancing interpretability.

Visualizations of training and validation curves further help in evaluating the model's behavior during learning. Additionally, the development of a simple prediction interface allows users to input any review and instantly receive sentiment results, making the system practical and user-friendly.

Overall, this project highlights the effectiveness of LSTM-based models in understanding and classifying customer opinions. Such sentiment analysis systems can be highly valuable in domains like customer service, product feedback monitoring, business analytics, and automated review interpretation.

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[1] Kim et al. (2021). *LSTM-based sentiment classification model for customer reviews demonstrating superior performance over traditional ML methods.*

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