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Customer Sentiment Analysis Using Machine Learning and Deep Learning Models for Product Reviews

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ABSTRACT: The effectiveness of the models is assessed using key performance metrics such as accuracy, precision, recall, and F1-score. This study underscores the promise of AI-powered sentiment analysis in delivering meaningful insights that help businesses better understand their customers. Sentiment analysis plays a vital role in modern business strategies, enabling companies to interpret customer sentiments and attitudes toward their offerings, whether products, services, or brands.

Key Words: Sentiment Analysis, Machine Learning, Customer Feedback, Natural language processing (NLP)

1.INTRODUCTION

Understanding customer sentiment through product reviews involves assessing the opinions, emotions, and attitudes that consumers express in their written feedback. This analysis plays a vital role for businesses looking to improve customer satisfaction, tailor product development, and enhance their marketing efforts. As e-commerce continues to grow, enormous amounts of unstructured data—including reviews, ratings, and user comments—are being generated daily across social media platforms and online service sites.

Due to the sheer volume and complexity of this data, manual analysis is no longer feasible. Automated sentiment analysis, also known as opinion mining, offers a solution by determining the emotional tone (positive, negative, or neutral) embedded within textual content. This technique helps organizations gain insights into customer experiences, track brand reputation, and detect common product or service issues.

1.1PROJECT PLAN

Analyzing customer sentiment in product reviews involves understanding and interpreting users' emotions, attitudes, and opinions as expressed in their written feedback. This analysis provides businesses with crucial insights to improve customer satisfaction, tailor product offerings, and fine-tune marketing strategies. As e-commerce platforms continue to expand, they generate massive amounts of unstructured data daily—from user reviews to ratings and comments on social media and online service platforms. Given the scale and complexity of this data, manual analysis is no longer feasible, which makes automated techniques essential for uncovering valuable insights.

Sentiment analysis, also known as opinion mining, is a method used to determine the emotional tone—positive, negative, or neutral—of textual content like product reviews. This tool allows companies to better understand consumer opinions, manage brand perception, and respond to recurring product or service issues. The evolution of machine learning (ML) and deep learning (DL) technologies has significantly enhanced sentiment analysis, especially in handling large-scale datasets. Deep learning models such as recurrent neural networks (RNNs) and transformer-based systems like BERT have proven highly effective in capturing the context and nuances of language, offering superior performance compared to earlier lexicon-based methods.

In e-commerce, online reviews play a critical role in shaping the relationship between buyers and sellers. Customers depend on the experiences of others to guide their purchase decisions, while businesses use this feedback to assess their strengths, uncover weaknesses, and monitor trends. Research shows that around 90% of consumers consider online reviews a vital part of their buying process, highlighting their importance in shaping consumer behavior. However, the massive number of reviews—especially for high-demand items like smartphones—poses a major challenge. A single popular model can attract thousands of reviews each month, making it nearly impossible to manually identify overall sentiment or specific product issues.

2. REVIEW ON LITERATURE

The rapid expansion of e-commerce has led to an exponential increase in user-generated content, particularly in the form of product reviews. These reviews have become a critical source of information for both consumers and businesses. Sentiment analysis, or opinion mining, has emerged as a key area of research aimed at extracting subjective information from textual data to evaluate customer opinions, emotions, and attitudes. The primary objective is to derive actionable insights that can guide product improvement, marketing strategy, and customer service.

Early approaches to sentiment analysis relied heavily on lexicon-based methods, where predefined dictionaries of opinion words were used to detect sentiment polarity. While these methods were intuitive and interpretable, they often failed to capture the contextual and semantic nuances of natural language, especially in complex or ambiguous texts. To address these limitations, machine learning (ML) techniques have been increasingly adopted.

Supervised learning algorithms such as Naïve Bayes, Support Vector Machines (SVM), and Decision Trees have shown considerable success in classifying sentiment. These models require labeled datasets for training and have demonstrated effectiveness when sufficient annotated data is available.

Unsupervised methods, such as clustering and topic modeling, are also employed, particularly in scenarios where labeled data is scarce.

2.1 EXISTING SYSTEM

In today's digital landscape, leading e-commerce platforms such as Amazon, Flipkart, and eBay accumulate a massive volume of customer feedback in the form of reviews. Despite this, many of these systems still rely on basic sentiment evaluation methods like star ratings or simple keyword detection, which often fall short of accurately interpreting the underlying emotions or opinions expressed by users.

1.Manual Review Moderation

A significant portion of platforms continue to use manual processes for reviewing and responding to customer feedback. This approach is labor-intensive and becomes inefficient when managing large-scale data.

2.Conventional Machine Learning Models

Techniques such as Linear Support Vector Classifiers and Random Forests are commonly employed.
These models typically require extensive feature engineering, like TF-IDF vectorization.
However, they often struggle to understand the deeper context or semantic nuances in review texts.

3.Limited Real-Time Sentiment Analysis

In most cases, sentiment analysis is performed on collected data in batches.
Real-time sentiment processing is not yet widely adopted across platforms.

2.2 PROBLEM STATEMENT

n the e-commerce sector, customers often share their thoughts and experiences through written product reviews. These reviews offer valuable insights into product performance, customer satisfaction, and areas that may require improvement. However, the sheer volume and unstructured nature of this data make it difficult for businesses to manually interpret and extract useful information.
To address this challenge, there is a growing need for an automated, accurate, and scalable solution capable of analyzing customer reviews using advanced Machine Learning (ML) and Deep Learning (DL) methods. An ideal system would not only classify sentiments (such as Positive, Negative, or Neutral) but also comprehend context to support businesses in making informed decisions aimed at enhancing customer satisfaction and refining product offerings.

Furthermore, with constantly changing customer expectations and trends in feedback, it is crucial to implement systems that can evolve and learn over time. Without an intelligent sentiment analysis framework, e-commerce companies risk missing essential insights, which could negatively impact customer retention, product development, and marketing effectiveness. Therefore, deploying a robust ML/DL-based sentiment analysis solution is vital for fully leveraging customer feedback.

3. METHODOLOGY

1.Data Acquisition

The dataset used for this study was sourced from Kaggle and can be accessed via the following link: https://www.kaggle.com/datasets/kalpchamey/e-commerce-phone-reviews. It contains essential information relevant to e-commerce smartphone reviews. The dataset consists of three main columns: the first includes the smartphone model names being reviewed, the second contains user-generated review texts describing performance, features, and overall experience, and the third lists user ratings on a scale of 1 to 5, reflecting satisfaction levels.

2.Data Loading

In this phase, the primary goal was to import the dataset and prepare it for further analysis. The data, which includes product reviews, was loaded from the specified source and stored in an appropriate structure to facilitate preprocessing and modeling.

3. Data Preprocessing

Preprocessing involved cleaning and preparing the textual data for sentiment analysis. The process included tokenizing the reviews, converting all text to lowercase, and correcting spelling errors. Common stop words such as "a," "an," and "with" were removed to reduce noise. Lemmatization was applied to reduce words to their root forms. Each review was then categorized as positive, negative, or neutral based on its rating. The dataset was divided into training and testing sets, with 70% used for training and the remaining 30% for testing

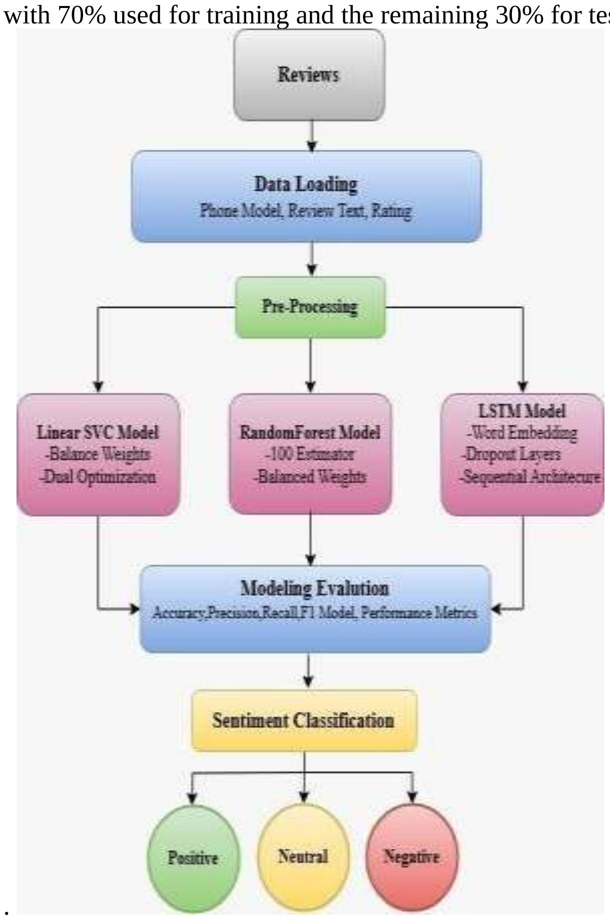

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Fig.no.1 .Workflow of proposed model

4. Modeling

Linear Support Vector Classifier (Linear SVC)

A Linear Support Vector Classifier is a type of machine learning model used primarily for classification tasks. It works by determining the best possible hyperplane that can divide text documents into sentiment categories—such as positive, negative, or neutral—within a high-dimensional feature space. These features are often derived from text representation techniques like TF-IDF or word embeddings, where each term forms a unique dimension in the feature vector.

Linear SVC is especially effective for sentiment analysis due to its ability to manage sparse and high-dimensional data efficiently. It's less prone to overfitting when compared to more complex models. The algorithm focuses on maximizing the margin between different sentiment classes by relying on support vectors the key data points that shape the decision boundary.

For multi-class sentiment classification, Linear SVC typically employs a "one-vs-rest" strategy. The linear nature of the model contributes to its computational efficiency and interpretability. The weight assigned to each feature provides insights into its contribution toward a particular sentiment prediction. Preprocessing steps such as stop word removal, lemmatization, and handling of negations are essential to improve the model's performance. Proper feature scaling and regularization are also important to ensure that no single feature skews the classification results.
This Linear SVC model configuration includes:

Balanced class weights to mitigate class imbalance
Dual formulation enabled for optimization
A maximum iteration limit of 10,000 for convergence

* Random Forest Model

Random Forest is a robust machine learning technique applicable to both classification and regression problems. It is part of the ensemble learning family and enhances performance by aggregating multiple models. The algorithm constructs a large number of decision trees, each trained on a random subset of the dataset and selected features. This randomness promotes diversity among the trees, which improves generalization and reduces overfitting.

Each tree is built using bootstrap sampling (sampling with replacement), and at each decision node, a random subset of features is evaluated for splitting. This further increases model diversity and reduces correlation among trees.

Random Forest models are effective for handling both categorical and numerical data, and they provide insights into feature importance. These models are known for achieving strong performance with minimal parameter tuning. In sentiment analysis, they are particularly beneficial because they can manage noisy language data and reduce overfitting thanks to their ensemble structure.

Configuration of the Random Forest model includes:
100 individual decision trees (estimators)
Balanced class weights to address uneven class distribution

* Long Short-Term Memory (LSTM)

LSTM, or Long Short-Term Memory networks, are a type of Recurrent Neural Network (RNN) well-suited for processing and analyzing sequential data such as text, speech, or time series. LSTMs are designed to capture long-term dependencies in data using specialized memory cells regulated by three gates: the input gate, forget gate, and output gate. These gates control what information should be stored, discarded, or output from the memory unit.

LSTM models are a form of deep learning that rely on extensive data for training. The more data the model is exposed to, the better its ability to capture patterns and make accurate predictions. They require considerable computational resources, especially during training.
For sentiment analysis, the LSTM model includes:
An embedding layer that converts words into 128-dimensional vectors
Two stacked LSTM layers with 128 and 64 units respectively
A dense hidden layer with 64 neurons
A final softmax layer that outputs probabilities across three sentiment classes: positive, neutral, and negative

.5 Model Evaluation

To assess the performance of the classifiers, several key metrics are used: accuracy, precision, recall, and F1-score.

Precision indicates the proportion of correctly predicted positive instances out of all predicted positive instances.

Recall measures the proportion of correctly predicted positive instances out of all actual positive instances.

F1-Score is the harmonic mean of precision and recall, offering a balance between the two.

Accuracy represents the proportion of total correct predictions (both positive and negative) to the overall number of predictions made.

6 Sentiment Classification

Sentiment classification refers to the task of assigning a sentiment label to a piece of text—such as a review, comment, or social media post. The sentiment classes typically include:

Positive: Text that conveys favorable or optimistic opinions.

Neutral: Text that is impartial or lacks a strong emotional tone.

Negative: Text expressing unfavorable or critical opinions.

3.1 PROPOSED SYSTEM

The proposed system aims to automate the analysis of customer sentiment in e-commerce product reviews using a combination of Machine Learning (ML) and Deep Learning (DL) techniques. The process begins with the collection of product reviews from online platforms, which are then passed through a text preprocessing pipeline involving steps like tokenization, stop-word removal, stemming or lemmatization, and normalization to clean and prepare the raw textual data. After preprocessing, The next step involves feature extraction using methods like TF-IDF, which convert text into numerical form suitable for modeling.

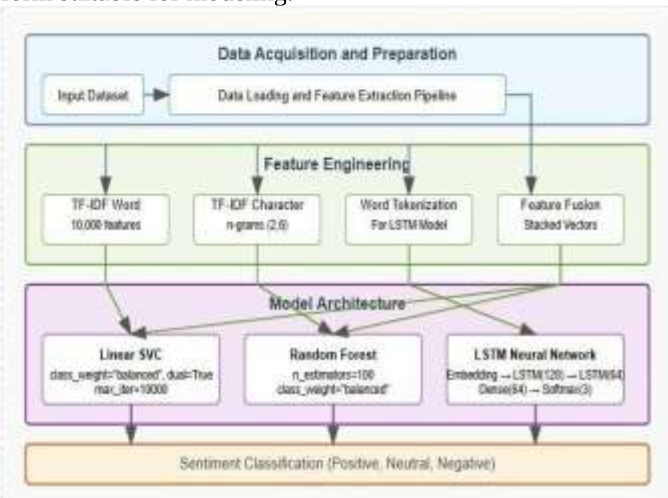

Fig no .2 Architecture of proposed system

4.CONCLUSION

The proposed sentiment analysis system uses LSTM networks along with smart data preparation techniques and performs better than traditional methods like Linear SVC and Random Forest. The LSTM model stands out because it has higher accuracy and a better F1-score. It can understand tricky parts of language, such as:The order of words in a sentence. Hidden meanings like sarcasm (e.g., saying ”great job” but meaning the opposite). Negative phrases (e.g., ”not good” instead of ”bad”). Older ML models often have a hard time with messy text or words specific to certain topics, but LSTM uses time-based patterns to improve its results. This makes it easier for businesses to get useful information from complicated customer feedback and act on it. Future research can focus on incorporating multimodal data, integrating textual reviews with visual data, such as product images or videos and user behavior such as clickstream data to provide a more comprehensive view of customer sentiment and enhance predictive accuracy. Furthermore, lightweight models optimized for edge devices can be explored for deployment on mobile apps. Continuous learning approaches may also help the model adapt to evolving language and customer preferences.

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