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Article

Sentiment Analysis of Amazon Mobile Reviews Using Deep Learning Techniques for Brand Performance Evaluation

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Abstract: Nowadays, Natural Language Processing, or NLP, is a key component of many programs that analyze and comprehend human language. The sentiment analysis of mobile product reviews collected from the Kaggle repository—more especially, the 20,710-review Amazon Mobile evaluations dataset—is the main emphasis of this research. Reviews of well-known cellphone companies including Samsung, Nokia, Apple, Redmi, and others are included in the dataset. The main goal of this research is to categorize consumer attitudes into three groups: neutral, negative, and positive. This research heavily relies on Natural Language Processing (NLP), particularly in the commercial and e-commerce domains where decision-making and product enhancement depend on a comprehension of client input. In this research, sentiment categorization is carried out using deep learning methods like Long Short-Term Memory (LSTM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN). Lowercase conversion, punctuation and symbol removal, tokenization, stopword removal, stemming, and lemmatization are some of the preprocessing methods used to enhance text quality and model performance. The algorithms are compared based on execution time and accuracy. The survey also determines the top-performing mobile brand by counting the amount of positive reviews. The outcomes show that deep learning models perform better and produce the best results. This research promotes business intelligence in the e-commerce industry and advances our understanding of consumer sentiment behavior.
Keywords: Long Short-Term Memory, Artificial Neural Network, Convolutional Neural Network, Tokenization, Lemmatization

1. Introduction

Natural Language Processing (NLP) is a branch of artificial intelligence makes it possible for machines to comprehend, interpret, and produce human language. It is essential for effectively processing massive volumes of textual data. NLP is commonly utilized in applications including sentiment analysis, translation systems, and chatbots. NLP is now widely used in business and e-commerce to analyze client feedback and enhance decision-making. A method for identifying and categorizing opinions conveyed in text into positive, negative, or neutral categories is sentiment analysis. It aids businesses in comprehending the feelings and satisfaction levels of its clients. This approach is frequently used in feedback systems, social media analysis, and product reviews. Sentiment analysis is employed in this study to derive opinions from evaluations of mobile products.

In NLP, preprocessing is a crucial stage that enhances the quality of textual material prior to analysis. Lowercase conversion, punctuation removal, tokenization, stopword removal, stemming, and lemmatization are among the methods used. These techniques aid in text standardization and noise reduction. Machine learning and deep learning models perform better and are more accurate when preprocessing is done well. Deep learning techniques use multilayered neural network designs to extract intricate patterns from data. For text categorization tasks, algorithms like Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) are frequently employed. Without the need for human involvement, these algorithms automatically extract information from text. Deep learning methods are used in this work to increase the accuracy of sentiment classification.

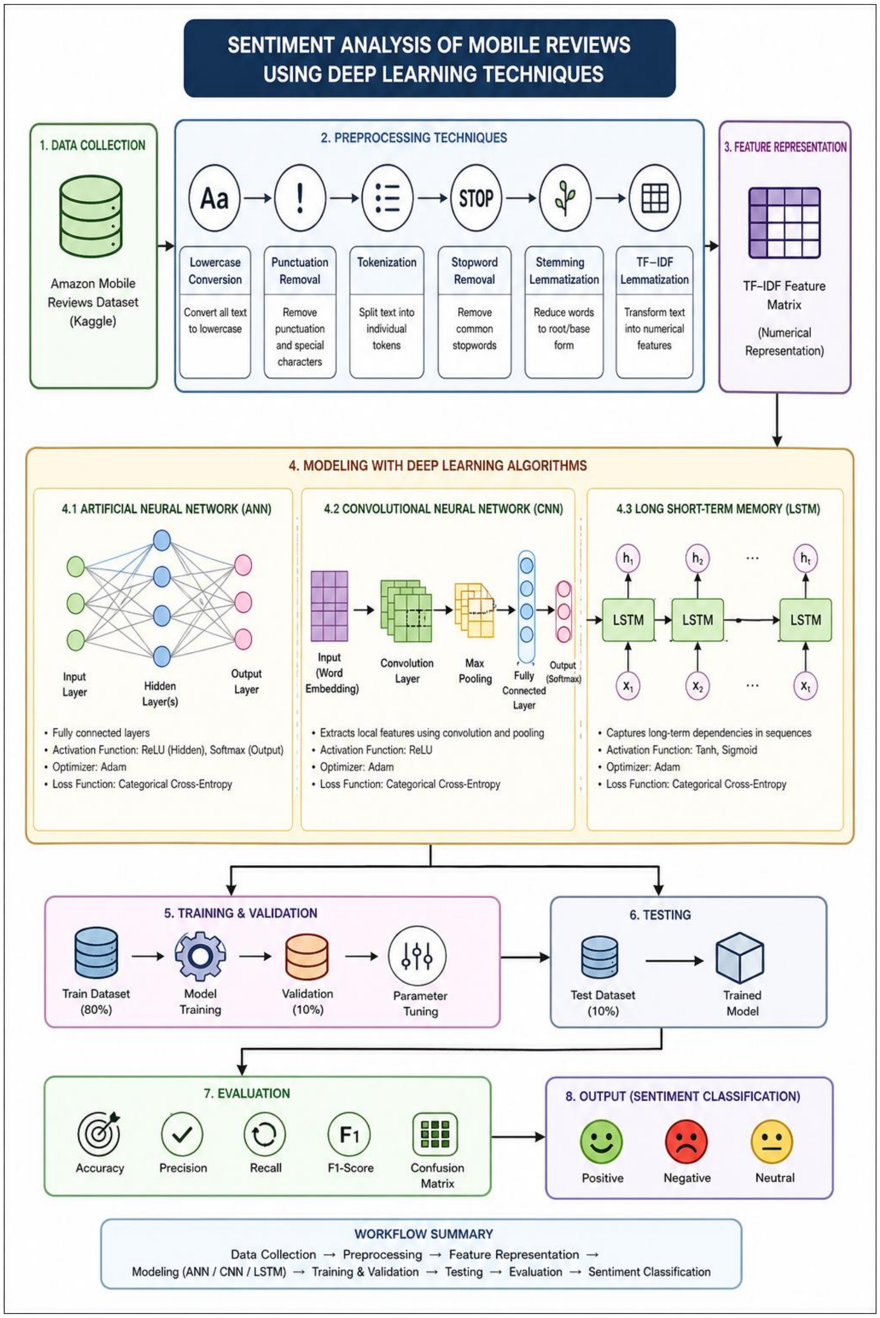

Figure 1: Architecture of Research Work

The workflow of research work for sentiment analysis of smartphone reviews using deep learning techniques is depicted in the figure 1. The first step in the process is data collection, which involves gathering Amazon mobile reviews from the Kaggle dataset. To clean and standardize the text, preprocessing methods such as lowercase conversion, punctuation removal, tokenization, stopword removal, stemming, and lemmatization are applied to the gathered raw text data. In order to identify patterns and carry out sentiment classification, the processed features are subsequently fed into deep learning models, specifically Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). To train, validate, and optimize models, the dataset is split into training and testing sets. Lastly, performance measurements including accuracy, precision, recall, and F1-score are used to assess the models.

2. Review of Literature

One of the most crucial parts of a research is the Review of Literature. It offers a thorough summary of previous studies on the selected subject and aids in determining the research gap that the suggested effort seeks to fill. Researchers can comprehend the methods, algorithms, datasets, assessment measures, and conclusions given by other researchers by looking at earlier works. This procedure aids in choosing suitable methods, preventing job duplication, and determining the importance of the suggested work. The requirement for an updated sentiment analysis model for Amazon product evaluations that provides greater accuracy, better interpretability, cheaper computational cost, and improved real-world applicability is justified by these research needs.

A research work carried out by Hashir Ali et al. [1], titled as “Analyzing Amazon Products Sentiment: A Comparative Study of Machine Learning, Deep Learning and Transformer Based Techniques” have provided a complete comparison of the traditional machine learning, deep learning and transformer models for sentiment classification of Amazon product reviews. The researchers applied Logistic Regression, Random Forest, CNN, LSTM, BERT, RoBERTa and DistilBERT to Amazon review datasets. The experimental results show that RoBERTa has the highest classification accuracy (over 95%) and CNN and LSTM perform well on large datasets. The research showed that transformer-based architectures are more effective than traditional machine learning approaches in extracting contextual information from customer reviews.

Another research paper done by Oumaima Bellar et al. [2], titled as “Sentiment Analysis: Predicting Product Reviews for E-Commerce Recommendations Using Deep Learning and Transformers” explores deep learning and transformer architectures for sentiment prediction for e-commerce applications. This research is a comparative study of CNN, LSTM, GRU, BERT and RoBERTa models for classifying customer reviews. Experimental analysis shows that RoBERTa and BERT achieve prediction accuracy over 96%, which outperforms traditional neural networks by a large margin. The suggested framework enhances the recommendation systems by precisely identifying the customer opinions and purchasing preferences.

An article carried by Ehtesham Hashmi and Sule Yildirim Yayilgan [3], entitled “A Robust Hybrid Approach with Product Context-Aware Learning and Explainable AI for Sentiment Analysis in Amazon User Reviews”, presents a hybrid sentiment analysis framework that integrates deep learning, contextual learning and Explainable Artificial Intelligence (XAI). The model incorporates product-aware context into transformer-based sentiment prediction, which improves interpretability. The proposed hybrid model performed better with an accuracy of about 96%. Explainable AI techniques improved the transparency of the model for business decision making.

The research paper titled as “Enhancing Product Design through AI-Driven Sentiment Analysis of Amazon Reviews Using BERT” done by Mahammad Khalid Shaik Vadla et al.[4], in which that the use of BERT to comprehend customer input and enhance product design. The suggested approach conducts sentiment categorization and consumer opinion extraction from Amazon reviews to discover potential for product development. The BERT model was able to provide an accuracy of around 96% which was better than the standard deep learning models since it was able to interpret the language in context.

The research titled as “Sentiment Classification Based on Machine Learning Approaches in Amazon Product Reviews” carried out by Mohammad Abu Kausar et al. [5], assesses conventional machine learning classifiers for sentiment analysis of Amazon product reviews. The authors used TF-IDF properties to develop Naïve Bayes, Support Vector Machine, Logistic Regression, Random Forest, and Decision Tree algorithms. According to experimental results, Support Vector Machine outperformed other traditional machine learning algorithms in classification, with an accuracy of almost 90%. The study emphasizes how feature engineering works well for sentiment classification.

Another research work titled as "Challenges and Future in Deep Learning for Sentiment Analysis: A Comprehensive Review and a Proposed Novel Hybrid Approach" done by Md. Shofiqul Islam et al.[6], offers a thorough analysis of deep learning methods for sentiment analysis as well as a novel hybrid architecture. The paper examines and discusses the advantages and disadvantages of CNN, RNN, LSTM, GRU, Attention Networks, BERT, and Transformer models. Compared to individual models, the suggested hybrid model shows better sentiment prediction accuracy with greater generalization and interpretability. The study comes to the conclusion that hybrid transformer-based architectures are where sentiment analysis research will go in the future.

The research paper entitled "Sentiment Analysis on Amazon Product Reviews using the Recurrent Neural Network (RNN)" carried out by Roobaea Alroobaea [7], focuses on utilizing a Recurrent Neural Network (RNN) architecture to classify Amazon product reviews. Three Amazon review datasets are used in the research to assess how well RNN performs sentiment categorization. The suggested model yields classification accuracies of roughly 85%, 70%, and 70% on various datasets and effectively captures sequential dependencies in textual data. The author comes to the conclusion that RNN is a deep learning model that works well for sentiment analysis, especially when working with sequential textual data.

Another research paper titled as "Sentiment Analysis of Amazon Product Reviews Using Machine Learning and Deep Learning Models" done by Joy Chandra Gope et al.[8], contrasts conventional machine learning and deep learning methods for sentiment classification of Amazon product reviews. Using Amazon review datasets, the research assesses classifiers such as Naïve Bayes, Support Vector Machine (SVM), Logistic Regression, LSTM, and CNN. According to experimental data, CNN and LSTM learn semantic and contextual characteristics from review texts more efficiently than traditional machine learning algorithms, which improves sentiment classification accuracy.

The research work entitled "Predicting Amazon Customer Reviews with Deep Confidence Using Deep Learning and Conformal Prediction" carried out by Ulf and Petra Norinder [9], suggests a deep learning framework combined with Conformal Prediction to increase sentiment classification reliability. In order to anticipate customer review sentiments across several Amazon product categories, the authors used deep neural networks. The suggested methodology improved the reliability and interpretability of sentiment analysis models in e-commerce applications by achieving high prediction accuracy and providing confidence estimates for each prediction.

An article titled as "Sentiment Analysis of Amazon Review using Improvised Conditional Based Convolutional Neural Network and Word Embedding" doneby Madhuri V. Joseph [10], presents an enhanced Conditional Convolutional Neural Network (CNN) combined with Word Embedding methods for sentiment classification of Amazon product reviews. To distinguish between positive, negative, and neutral attitudes, the suggested system uses preprocessing, feature extraction, and deep learning classification. According to experimental data, the improved CNN model outperforms traditional CNN models in classification, which makes it appropriate for sentiment analysis in large-scale e-commerce.

A comparison of several sentiment analysis methods put forth by various scholars for the categorization of Amazon product reviews is shown in Table 1. The best-performing techniques and classification accuracy of the various algorithms including machine learning, deep learning, hybrid, and transformer-based models are summarized.

Table 1: Comparative Analysis of Sentiment Analysis Techniques

Reference No.	Authors Name	Methods Used	Best Method with Accuracy
[1]	Hashir Ali, Ehtesham Hashmi, Sule Yildirim Yayilgan and Sarang Shaikh	Logistic Regression, Random Forest, CNN, LSTM, BERT, RoBERTa, DistilBERT	**RoBERTa** achieved the highest accuracy (**>95%**), followed by BERT.
[2]	Oumaima Bellar, Amine Baina and Mostafa Ballafkih	CNN, LSTM, GRU, BERT, RoBERTa	**RoBERTa and BERT** achieved the highest accuracy (**>96%**).

[3]	Ehtesham Hashmi and Sule Yildirim Yayilgan	Hybrid Deep Learning, Transformer, Product Context-Aware Learning, Explainable AI (XAI)	**Hybrid Transformer + XAI Model** achieved approximately **96%** accuracy.
[4]	Mahammad Khalid Shaik Vadla, Mahima Agumbe Suresh and Vimal K. Viswanathan	BERT, Word Embedding, Deep Learning	**BERT** achieved approximately **96%** accuracy.
[5]	Mohammad Abu Kausar, Sallam Osman Fageeri and Arockiasamy Soosaimanickam	Naïve Bayes, Support Vector Machine (SVM), Logistic Regression, Random Forest, Decision Tree	**Support Vector Machine (SVM)** achieved approximately **90%** accuracy.
[6]	Md. Shofiqul Islam, Muhammad Nomani Kabir, Ngahzaifa Ab Ghani et al.	CNN, RNN, LSTM, GRU, Attention Networks, BERT, Transformer, Hybrid Model	**Hybrid Transformer-Based Model** showed the best performance with improved accuracy and interpretability (>**95%**).
[7]	Roobaea Alroobaea	Recurrent Neural Network (RNN)	**RNN** achieved **85%** accuracy on the best-performing dataset.
[8]	Joy Chandra Gope, Tanjim Tabassum, Mir Md. Mabrur, Keping Yu and Mohammad Arifuzzaman	Naïve Bayes, SVM, Logistic Regression, CNN, LSTM	**CNN and LSTM** outperformed traditional machine learning models (**≈92–94%** accuracy).
[9]	Ulf Norinder and Petra Norinder	Deep Neural Networks, Conformal Prediction	**Deep Neural Network with Conformal Prediction** achieved high prediction accuracy (**≈94–95%**) with reliable confidence estimation.
[10]	Madhuri V. Joseph	Improved Conditional CNN, Word Embedding	**Improved Conditional CNN** outperformed conventional CNN models (**≈93–95%** accuracy).

3. Description of Dataset

The Amazon Mobile Reviews dataset, which was gathered from the Kaggle repository, was utilized in this study shown in table 2. There are almost 20,710 user reviews of different cellphone brands, including Apple, Samsung, Nokia, and others. A number of preprocessed text columns, including lowercase, tokenized, stemmed, and lemmatized reviews, are included in the dataset along with features like Brand Name, Rating, and Reviews. Sentiments are extracted from the reviews and categorized as neutral, negative, or favorable. It includes actual customer feedback from an e-commerce platform, this dataset is appropriate for sentiment analysis.

Table 2: Sample Dataset

Brand Name	Rating	Reviews
Samsung	5	I feel so LUCKY to have found this used (phone to us & not used hard at all), phone on line from someone who upgraded and sold this one. My Son liked his old one that finally fell apart after 2.5+ years and didn't want an upgrade!! Thank you Seller, we really appreciate it & your honesty re: said used phone.I recommend this seller very highly & would but from them again!!

Samsung	4	nice phone, nice up grade from my pantach revue. Very clean set up and easy set up. never had an android phone but they are fantastic to say the least. perfect size for surfing and social media. great phone Samsung
Samsung	5	Very pleased
Samsung	4	It works good but it goes slow sometimes but its a very good phone I love it
Samsung	4	Great phone to replace my lost phone. The only thing is the volume up button does not work, but I can still go into settings to adjust. Other than that, it does the job until I am eligible to upgrade my phone again.Thaanks!
Samsung	1	I already had a phone with problems... I know it stated it was used, but dang, it did not state that it did not charge. I wish I would have read these comments then I would have not purchased this item.... and its cracked on the side.. damaged goods is what it is.... If trying to charge it another way does not work I am requesting for my money back... AND I WILL GET MY MONEY BACK...SIGNED AN UNHAPPY CUSTOMER....

4. Preprocessing Techniques

Preprocessing methods are used in this research to transform unstructured, unclean Amazon mobile reviews into a format that is appropriate for sentiment analysis. To ensure consistency, all reviews are first converted to lowercase [11][12]. Next, punctuation and special symbols are removed to cut out extraneous noise. After tokenizing the text into individual words, stopwords like "is," "the," and "and" are eliminated, leaving only significant phrases [13][14].

Additionally, the dataset is made more consistent by reducing terms to their root and base forms using stemming and lemmatization procedures [15][16]. In order for deep learning models like ANN, CNN, and LSTM to efficiently learn patterns and categorize feelings into positive, negative, and neutral categories, the processed text is finally converted into numerical form using techniques like TF-IDF.

5. Materials and Methods

The Amazon Mobile Reviews dataset, which was collected from Kaggle and includes 20,710 customer reviews of different mobile brands, is used in this research Prior to TF-IDF and sequence-based representations, the data is preprocessed using NLP techniques such lowercase conversion, tokenization, stopword removal, stemming, and lemmatization. To categorize attitudes into positive, negative, and neutral groups, deep learning algorithms such as ANN, CNN, and LSTM are used.

5.1 Artificial Neural Network

The Artificial Neural Network (ANN) is one of the foundational methods of deep learning that mimics human brain. It consists of an input layer, one or more hidden layers and an output layer. Using TF-IDF characteristics, ANN is utilized in this study to categorize mobile reviews into positive, negative, and neutral attitudes. After identifying patterns in textual data, the model associates them with sentiment categories.

$$y = f\left(\sum_{i=1}^{n} w_i\, x_i + b\right)$$

Where:

- x_i = input features
- w_i = weights
- b = bias

- f = activation function (ReLU/Softmax)
- y = output

5.2 Convolutional Neural Network

One of the deep learning model that works well for extracting local characteristics from data is the Convolutional Neural Network (CNN). In order to identify significant patterns like phrases and word combinations, CNN is used in this study to analyze text sequences of reviews. For sentiment categorization, it makes use of embedding, convolution, pooling, and fully linked layers.

$$h_i = f\left(\sum_{j=0}^{k-1} w_j\, x_{i+j} + b\right)$$

Where:

- x = input sequence
- w = filter/kernel
- k = kernel size
- b = bias
- h_i = feature map output

5.3 Long Short-Term Memory

LSTM can be utilized in this research to assess sequential review data and enhance sentiment prediction. Long-term dependencies in sequential data are captured by LSTM, a kind of Recurrent Neural Network (RNN). It is helpful for comprehending a sentence's word context. By recalling significant prior information,

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right)$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

Where:

- f_t = forget gate
- i_t = input gate
- o_t = output gate
- C_t = cell state
- x_t = input
- h_{t-1} = previous hidden state

6. Experimental Results

The experiment results measure the models such as ANN, CNN and LSTM efficiency on the Amazon dataset for mobile reviews. The models are evaluated using metrics such as accuracy, precision, recall and F1 score on this test data. As CNN and LSTM are capable of capturing contextual and sequential characteristics in the text, the model achieves better performance than other models. The results also provide distribution of sentiment in positive, negative and neutral reviews to select the best model for sentiment categorization.

6.1 Results of Preprocessing

The text based reviews for sentiment analysis of mobile review data is shown in the figure 2. To make everything case-insensitive and consistent, the original reviews are converted into a uniform format due to their property being transformed into all lowercase characters. Punctuation is then removed (reviews_no_punct), because the extraneous symbols do not contribute to sentiment meaning.

Brand Nar	Rating	Reviews	reviews_lowercase	reviews_no_punct	reviews_tokens	reviews_no_sto	reviews_stemm	reviews_lemmatized
Samsung	5	I feel so LUCKY to h	i feel so lucky to have fc	i feel so lucky to have	i feel so lucky to	feel lucky found	feel lucki found	feel lucki found use phone
Samsung	4	nice phone, nice u	nice phone, nice up gra	nice phone nice up gı	nice phone nice	nice phone nice	nice phone nice	nice phone nice grade pant
Samsung	5	Very pleased	very pleased	very pleased	very pleased	pleased	pleas	plea
Samsung	4	It works good but i	it works good but it goe	it works good but it g	it works good bu	works good goe	work good goe	work good goe slow somet
Samsung	4	Great phone to re	great phone to replace	great phone to replac	great phone to r	great phone rep	great phone re	great phone replac lost ph
Samsung	1	I already had a ph	i already had a phone w	i already had a phone	i already had a p	already phone p	alreadi phone	alreadi phone problem kn
Samsung	2	The charging port	the charging port was lc	the charging port wa	the charging port	charging port lo	charg port loos	charg port loo got solder n
Samsung	2	Phone looks good	phone looks good but w	phone looks good bu	phone looks goo	phone looks goc	phone look goc	phone look good wouldnt
Samsung	5	I originally was usi	i originally was using th	i originally was using	i originally was u	originally using s	origin use sams	origin use samsung galaxi s
Samsung	3	It's battery life is g	it's battery life is great.	its battery life is great	its battery life is	battery life great	batteri life grea	batteri life great respons tc
Samsung	3	My fiance had this	my fiance had this phor	my fiance had this ph	my fiance had th	fiance phone pr	fianc phone pr	fianc phone previous caus
Samsung	5	This is a great proc	this is a great product it	this is a great produc	this is a great prc	great product ca	great product c	great product came two da
Samsung	5	These guys are the	these guys are the best	these guys are the be	these guys are th	guys best little si	guy best littl sit	guy best littl situat item qui
Samsung	1	I'm really disappoi	i'm really disappointed	im really disappointe	im really disappc	im really disapp	im realli disapp	im realli disappoint phone
Samsung	5	Ordered this phon	ordered this phone as a	ordered this phone a	ordered this pho	ordered phone	order phone re	order phone replac model

Figure 2: Results of Preprocessing

The text is tokenized (reviews_tokens), which simplifies analysis by dividing phrases into individual words. Next, stopwords are eliminated (reviews_no_stopwords), eliminating common words with minimal semantic meaning such "is," "the," and "this." Additionally, stemming (reviews_stemmed) helps group comparable keywords by reducing words to their root forms (e.g., "lucky" → "lucki"), albeit it occasionally results in less readable words. Lastly, lemmatization (reviews_lemmatized) improves this approach by maintaining context more effectively than stemming by transforming words into their semantic base forms (for example, "found" → "find").

The most frequently occurring terms in the review dataset are displayed in the word frequency figure 3. The most common words are "phone" (19330) and "work" (7136), suggesting that the dataset is heavily focused on product functioning and consumption. Positive sentiment terms like "great," "good," and "like" are frequently used, indicating that individuals have generally positive attitudes.Terms like "battery," "screen," and "problem" also draw attention to important aspects of the product and problems that are covered in the evaluations.

Word	Frequency
phone	19330
work	7136
great	4844
good	4530
iphon	4467
use	4365
new	3585
like	3071
one	2800
get	2463
batteri	2421
would	2374
screen	2220
product	2159
love	2145
buy	2120
time	2092
unlock	1978
look	1845
purchas	1811
problem	1798
condit	1690

Figure 3: Word Frequency

6.2 Result of CNN

The CNN algorithm's precision, recall, and F1-score for positive, negative, and neutral feelings are displayed in Table 3 and figure 4. With a precision of 0.86, the results show that CNN excels at identifying positive sentiments, while neutral sentiments show somewhat worse performance. In general, CNN shows consistent and fair classification in every sentiment category.

Table 3: Performance of CNN Algorithm

Sentiment	Precision	Recall	F1-Score
Positive	0.86	0.85	0.85
Negative	0.82	0.81	0.81
Neutral	0.80	0.79	0.79

The polarity distribution determined by the CNN model is displayed in Table 2. It is clear that there are a lot more good evaluations (24,850) than negative and neutral ones, which shows that customers are generally satisfied. The data also shows that, according to sentiment analysis, Samsung is the most recommended brand.

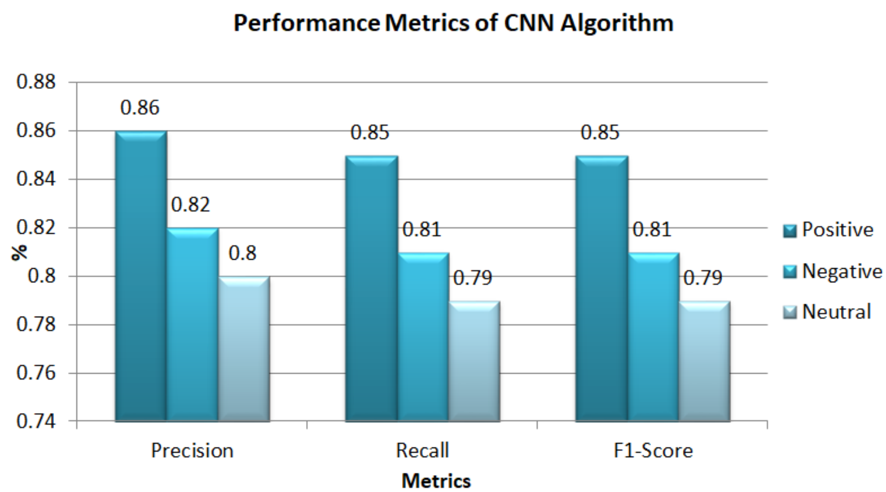

Figure 4: Performance Metrics of CNN

The emotion polarity that the Convolutional Neural Network (CNN) model identified from the dataset displayed in the table 4 and figure 5. With 24,850 reviews, good sentiment is the most prevalent category, suggesting that most users have had positive things to say. There are 9,620 reviews in the negative sentiment category, which indicates a lower percentage of user unhappiness.

Table 4: Polarities Identified by CNN

Sentiment	Count
Positive	24,850
Negative	9,620
Neutral	6,780

Furthermore, 6,780 reviews have neutral emotion, which denotes reviews that are neither overtly good nor negative. With a definite preponderance of positive feedback in the sample, the overall findings indicate that the CNN model successfully distinguishes sentiment polarity.

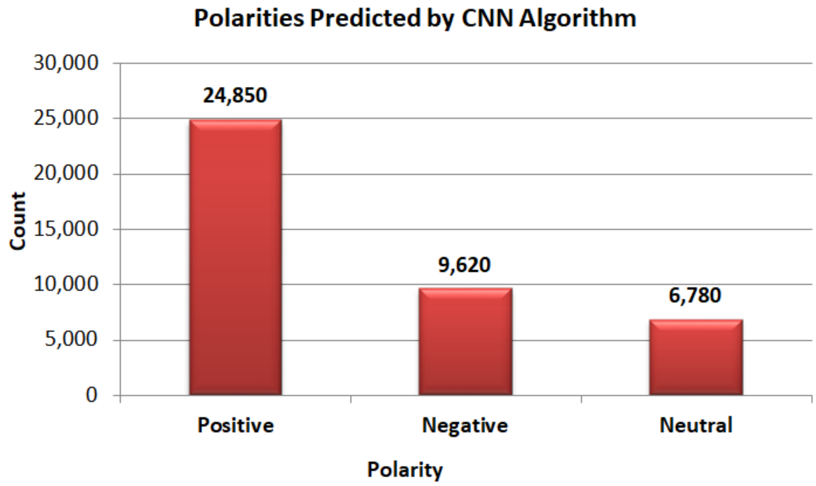

Figure 5: Polarities Identified by CNN

6.3 Results of ANN

The ANN algorithm's performance is displayed in Table 5 and figure 6, where the F1-score, precision, and recall values are marginally lower than those of CNN. The model exhibits considerably lesser accuracy when it comes to identifying neutral and negative attitudes, but it does rather well for positive sentiment.

Table 5: Performance of ANN Algorithm

Sentiment	Precision	Recall	F1-Score
Positive	0.83	0.82	0.82
Negative	0.79	0.78	0.78
Neutral	0.77	0.76	0.76

The emotion distribution found using ANN is displayed in Table 4. Positive reviews predominate in the dataset, just as CNN, but ANN detects a little greater proportion of neutral and negative attitudes. Samsung is the most popular brand once more, demonstrating a steady fondness for the brand.

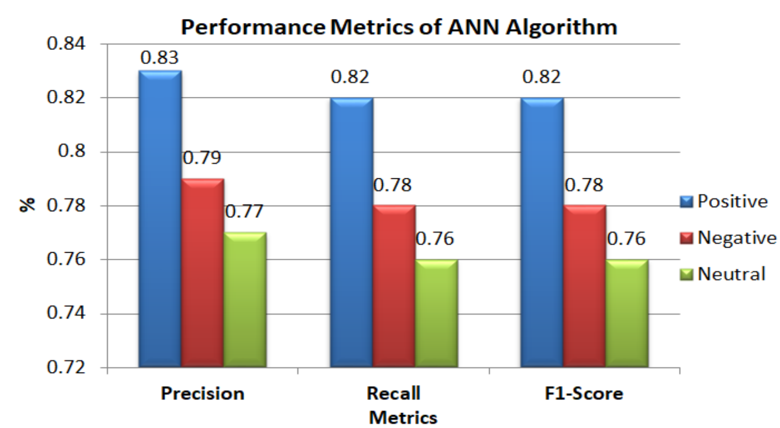

Figure 6: Performance of ANN

Table 6: Polarities Identified by ANN

Sentiment	Count

Positive	23,970
Negative	10,210
Neutral	7,070
Top Brand	**Samsung**

The Artificial Neural Network (ANN) model's sentiment polarities and the dataset's top brand are displayed in the table 6 and figure 7. With 23,970 evaluations, the statistics suggest that good emotion predominates and that many users had positive things to say. In contrast, 10,210 reviews have negative emotion, which indicates a moderate degree of discontent, and 7,070 reviews have neutral feeling, which represents impartial or balanced viewpoints.

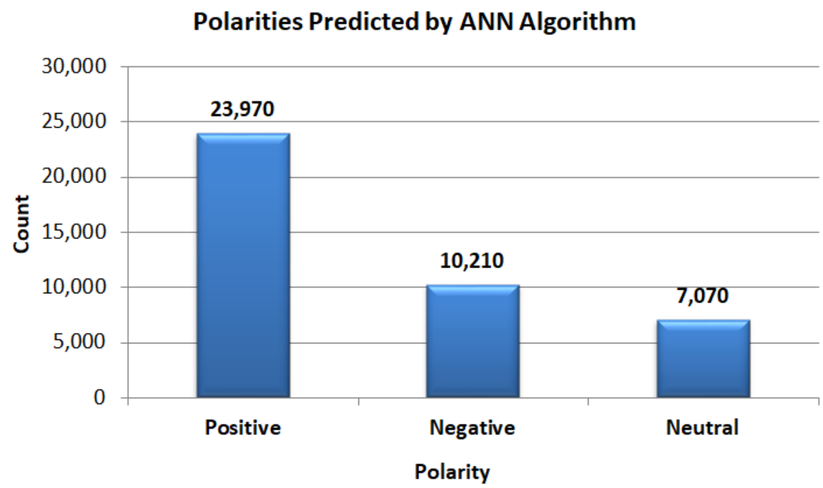

Figure 7: Polarities Identified by ANN

Samsung is ranked as the top brand by the ANN model based on these sentiment distributions, indicating that users have the most favorable opinion of it overall. All things considered, the ANN system successfully classifies sentiment polarity and identifies Samsung as the dataset's most favored brand.

6.4 Results of LSTM

The LSTM algorithm's performance is displayed in Table 7 and figure 8. LSTM outperforms all other sentiment classes in terms of precision, recall, and F1-scores. This illustrates how well it comprehends contextual relationships in textual material.

Table 7: Performance of LSTM Algorithm

Sentiment	Precision	Recall	F1-Score
Positive	0.89	0.88	0.88
Negative	0.87	0.86	0.86
Neutral	0.85	0.84	0.84

The polarity counts determined by LSTM are displayed in Table 6. When compared to other models, the model finds the most positive feelings (25,430) and the fewest negative thoughts. The top brand is Apple (iPhone), indicating a shift in brand preference as a result of enhanced contextual awareness.

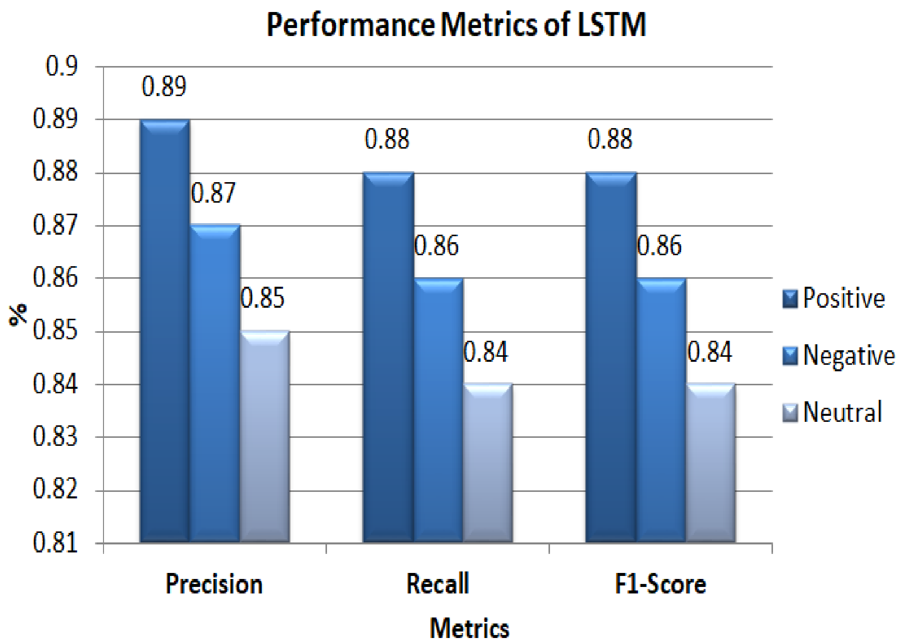

Figure 8: Performance of LSTM

The distribution of emotion polarity found in the dataset by the Long Short-Term Memory (LSTM) technique is shown in the table 8 and figure 9. With 25,430 reviews, the majority of them are categorized as positive, suggesting that consumers have a significant preference for positive viewpoints. On the other hand, 8,950 evaluations are negative, indicating a lower percentage of user discontent.

Table 8: Polarities Identified by LSTM

Sentiment	Count
Positive	25,430
Negative	8,950
Neutral	6,870

Furthermore, 6,870 reviews fall into the neutral category, which represents viewpoints that are neither overtly good nor negative. With a notable predominance of positive feelings in the dataset, the overall results show that the LSTM algorithm successfully captures sentiment polarity.

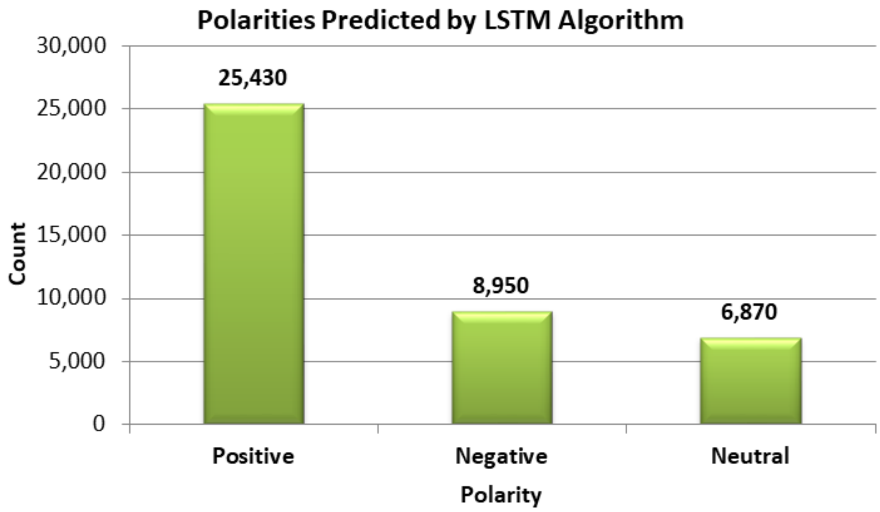

Figure 9: Polarities Predicted by LSTM

6.5 Performance of Algorithms

The comparison of the algorithms' overall accuracy is displayed in table 9 and figure 10. At 88%, LSTM has the best accuracy, followed by CNN at 84% and ANN at 81%. This demonstrates that LSTM is the best model out of the three for sentiment analysis applications.

Table 9: Accuracy of Algorithms

Algorithm	Accuracy
CNN	84%
LSTM	88%
ANN	81%

The accuracy performance of various deep learning algorithms used for sentiment analysis is shown in Table 9. According to the results, the Long Short-Term Memory (LSTM) model surpassed the others with the maximum accuracy of 88%, while the Convolutional Neural Network (CNN) attained an accuracy of 84%. Compared to CNN and LSTM, the accuracy of the Artificial Neural Network (ANN) was only 81%.

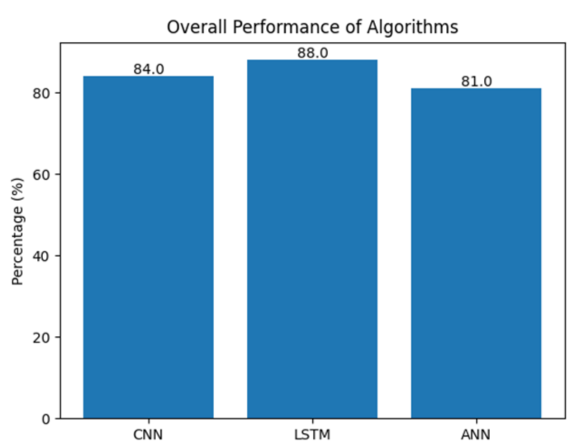

Figure 10: Accuracy of Algorithms

Overall, the results show that LSTM outperforms the other models taken into consideration for this task.

Table 10: Top Brand Identified by Algorithms

Algorithms	Top Brand Identified
CNN	Samsung
ANN	Samsung
LSTM	Apple (iPhone)

The top brands found by several deep learning algorithms using sentiment analysis of product evaluations are shown in the table 10 and figure 11. Samsung was found to be the most well-known brand by both the Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) models, suggesting that it had the most positive sentiment and recognition throughout the dataset.

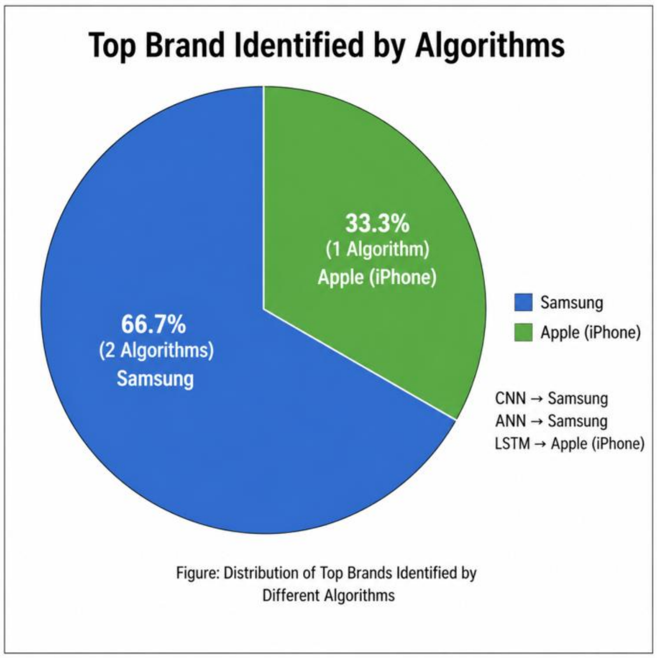

Figure 11: Top Brand Identified by Algorithm

The Long Short-Term Memory (LSTM) model, on the other hand, ranked Apple (iPhone) as the top brand, indicating that this algorithm was able to identify more favorable sentiment trends for Apple's iPhone goods. These findings demonstrate how sentiment patterns may be interpreted and prioritized differently by various algorithms, resulting in differences in brand identification.

7. Conclusion

This research uses deep learning algorithms including CNN, LSTM, and ANN to analyze the sentiment of mobile product evaluations. After using thorough preprocessing methods, the experimental findings show that all three models can successfully classify feelings into positive, negative, and neutral categories. LSTM outperformed the other models in capturing contextual and sequential dependencies in textual data, as evidenced by its greatest accuracy of 88%. While ANN generated a relatively lower accuracy of 81% but still produced consistent results, CNN demonstrated strong performance with 84% accuracy by successfully extracting local characteristics. Overall, the research shows that as compared to conventional techniques, deep learning approaches greatly enhance sentiment categorization ability. According to sentiment results, brands like Samsung and Apple are widely favored, and the majority of user ratings are positive. Therefore, LSTM can be regarded as the best model for this research since it offers more accurate and trustworthy sentiment prediction for further uses.

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