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(Research Article)

Data-driven product marketing strategies: An in-depth analysis of machine learning applications

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Abstract

Marketing is a planned method of creating, communicating, delivering, and exchanging valuable solutions for customers, clients, partners, and society as a whole. Machine learning techniques may completely dominate the market based on big data analysis, whereas traditional measuring tools fail to capture the market value of big data. Using a high-level overview and implementation process, this article explains how ML is being used in marketing. The purpose of this paper is to deliver the findings of an investigation into the connection between marketing strategy and the creation of successful new products over the long term. This study presents an in-depth analysis of marketing product strategies through an application of ML models, specifically CNN-LSTM, DT, and SVM. Utilizing the Amazon Product Review dataset, the research involves extensive data preprocessing, including steps like tokenization and stop word removal, followed by the splitting of data. The models' performance is evaluated using metrics including F1-score, recall, accuracy, and precision. The CNN-LSTM outperformed the others with a 94% accuracy rate, while Logistic Regression achieved the lowest at 70%. The research highlights the value of sophisticated machine learning models for improving marketing tactics, leading to better marketing-related decision-making.

Keywords: Analysis of Marketing; Marketing Product; Marketing Strategies; Depth-analysis; Machine Learning

1. Introduction

Advertising is only one component of marketing, and certainly not its most important one, but this misconception persists since marketing encompasses all of it. When a business engages in any and all actions aimed at increasing awareness of, and demand for, its goods and services among target audiences, this is known as marketing. There are four main tiers to marketing decisions in the conventional marketing mix: product, pricing, promotion, and location (1). To convey persuasive messages to customers, marketing is crucial. Offering persuasive arguments in an effort to influence consumer decisions is one marketing tactic. Just so you know, from the customer's point of view, this works well for the high-engagement product. In addition, with so many items on the market, this effect is crucial. There is a plethora of options for the consumer to choose the good that best suits their need (2)(3). Thus, the buyer is in a stronger position to choose and settle on the best product for their needs. To influence a customer's purchasing behaviour all the way up to the decision-making stage, the correct marketing strategy is essential. Customers' impressions of the manufacturer have an impact on their purchasing decisions (4). Making each product supplied to clients more valuable is the objective of value-based marketing. Basically, value-based marketing is all about finding innovative ways to make customers happy. Opportunities for producers and consumer requirements already in existence might give rise to a value-based marketing approach. Production may go into the red or even break even for a while when adding satisfaction values (5). A marketing strategy is a way for a business or organisation to use its limited resources in order to attract more customers, boost sales, and gain a competitive edge (6). When a business analyses its strategic initial situation and formulates, evaluates, and selects market-oriented strategies, it engages in marketing strategy, which

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encompasses all fundamental and long-term marketing activities. This strategy helps the business achieve its goals and marketing objectives (7)(8). The marketers' job was to gather the data and figure out whether it was applicable. In the next step, marketers formulate theories, put them to the test, assess their performance, and draw conclusions. In comparison to machine learning, human humans have limited working hours and a large computational capacity, both of which are drawbacks when it comes to solving target marketing problems. AI systems that can acquire new skills and knowledge via exposure to new data and experiences are the focus of ML(9)(10). Machine learning allows marketers to analyse data with significant values that would be too complex for humans to handle(11).

Figure 1 Marketing Strategy

1.1. Contribution of the study

This study aims to show the depth-analysis of marketing product strategies based on ML techniques.

Some of the key contributions of this study are described below:

- Introducing a comprehensive methodology leveraging machine learning models for in-depth analysis of marketing product strategies.
- Showing that the CNN-LSTM hybrid model outperforms more conventional models like DT, and SVM according to F1-score, recall, accuracy, and precision.
- Providing comprehensive assessment measures, like confusion matrix, precision, recall, accuracy, and F1-score, to provide insights into consumer sentiment prediction.
- Offering actionable insights for businesses to develop robust marketing strategies based on the analysis of Amazon product reviews.

1.2. Structure of paper

This is how the rest of the paper is organised. Section 2 delivers the background information on product marketing methods. Section 3 presents the strategy, Section 4 presents the findings analysis and discussion, and there was a debate. Finally, the study's conclusion and future directions are provided in Section 5.

2. Literature Review

In this part, provide some previous work on depth-analysis of marketing product strategies based on ML Methods.

In this research, Lavanya, Shenoy and Venugopal, (2023) With the use of the Yelp dataset including restaurant reviews, this study evaluates several words embedding methods, including TF-IDF, Glove, Word2Vec, and Doc2Vec. SVM and LR are two examples of supervised ML algorithms. Performance measures including Precision, Accuracy, F1-Score, and Recall are used to gauge the algorithms' effectiveness. Comparative results show that 98% of the results were achieved using a combination of TF-IDF word embedding approach and SVM(12).

This study, Van, (2023) takes a distinctive approach by employing two machine learning models, Random Forest and XGBoost, to leverage technical analysis features for model enhancement. Additionally, they introduce a trading strategy rooted in technical analysis, which utilises support and resistance zones to help investors minimise risks and optimise profits. An experimental outcome showed that a proposed method yielded a profit of 13.33%, which is higher than the baseline model's profit of 10.38%. The positive outcomes of this study provide strong motivation to implement variations of this approach in more advanced ML and DL models(13).

A primary aim of the research, Mathanprasad and Gunasekaran, (2022) is to investigate the present values of stock market data derived from real-time data, where the value of stock market data varies with time. Researchers still find predicting stock market movements and evaluating potential stock price movements to be a difficult and tricky problem. Current study is driven by the fact that stock market data values fluctuate over time in relation to topic risk. The stock exchange's forecast accuracy has been enhanced to 94.17% with the use of ML techniques(14).

This research work by Sharma et al. (2022), is to sort the tweets sent by American aircraft passengers into a favourable and bad category so that other people may use this knowledge to make judgements about their own journeys. The task was completed by using three ML classifiers to categories the tweet data obtained from the Kaggle site. Experimental findings show that compared to the LR and MNB baselines, SVM achieves an accuracy of 6.23 percent and a performance of 0.9 percent, respectively(15).

In this research, Tusar and Islam, (2021) it's a method that uses both ML and NLP. One common application of sentiment analysis is to glean information about how the general public feels about certain issues, goods, or services. With the goal of developing a reliable method for SA on a massive, unbalanced, and multi-classed dataset, the authors of this study employed many ML classification algorithms, including SVM, RF, MNB, LR, and Bow and TF-IDF, respectively. By combining SVM and LR with the Bag-of-Words methodology, our top methods achieve an accuracy rate of 77%(16).

Table 1 Related Work Table on Depth-Analysis of Marketing Product Strategies on Machine Learning

References	Methodology	Dataset	Performance	Limitations & Future Work
Lavanya, Shenoy and Venugopal	Evaluated various word embedding techniques (Bow, TF-IDF, Glove, Word2Vec, Doc2Vec) combined with ML methods (LR, SVM)	Yelp dataset for restaurant reviews	Best performance: SVM with TF-IDF, accuracy of 98%	Future work could explore deeper neural network models and extend analysis to other review datasets.
Van	Utilised Random Forest and XGBoost models with technical analysis features, introduced a trading strategy using support and resistance zones.	Stock market data for technical analysis	Profit of 13.33%, compared to the baseline model's profit of 10.38%	Future research could implement advanced ML and deep learning models and explore other financial indicators.
Mathanprasad and Gunasekaran	Analysed real-time stock market data using ML algorithms for stock prediction	Real-time stock market data	Prediction accuracy improved to 94.17%	AdaBoost, Decision Trees, K-Nearest Neighbours, Support Vector Machines, and Feedforward Neural Networks are the foundation models (90.6%–91.7%).
Sharma	Classified tweets of American flight travellers into positive and negative classes using SVM, LR, and MNB classifiers	Kaggle dataset of American flight travellers' tweets	SVM outperformed LR and MNB by 0.9% and 6.23% accuracy, respectively	Future work might explore more complex models like deep learning and expand the dataset to include more varied sources of tweets.

Tusar and Islam	Combined NLP techniques (Bow, TF-IDF) with ML classifiers (SVM, LR, MNB, RF) for sentiment analysis	Large, imbalanced, multi-class dataset for sentiment analysis	Best performance: SVM and LR with Bow, achieving 77% accuracy	Future research could focus on handling class imbalance more effectively and explore advanced NLP techniques like transformer models.

2.1. Research gaps

The research works collectively indicate significant improvement in various uses of machine learning and NLP, such as stock market prediction, sentiment analysis, and tweet classification. However, there is a dearth of study in the use of complex DL models namely transformers and RNN, which has shown great performance in various NLP applications. Additionally, the capacity of models to scale across different datasets and domains, as well as the handling of unbalanced datasets, have not been explored in depth enough. Adding DL structures, enhancing techniques for dealing with class imbalance, and testing the models on diverse and large datasets to ensure their durability and applicability should be the main goals of future research in order to overcome these weaknesses.

3. Methodology

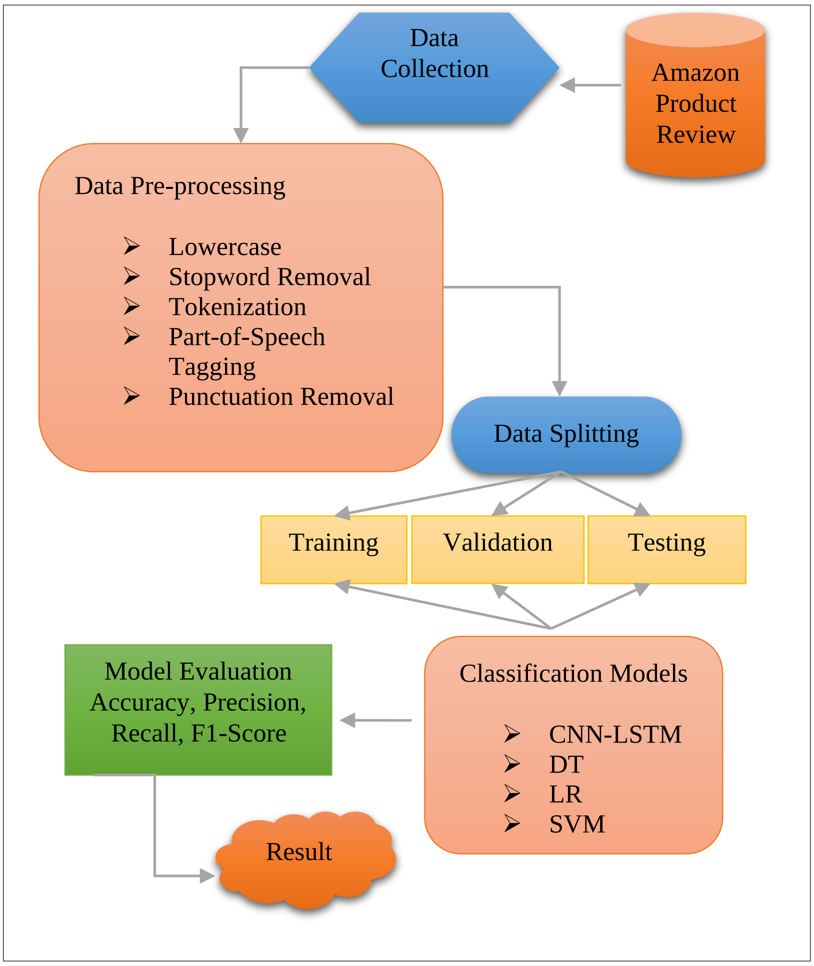

Figure 2 Data Flow Diagram

The method taken to accomplish the goal of this study entails the systematic evaluation of marketing product strategies by employing machine learning models. The process starts with data acquisition where the Amazon product review dataset in JSON format is obtained which consists of different electronics' reviews. Data preprocessing comes. Next; steps involved are converting the text to lowercase, eliminating stop words, text to tokenisation, part of speech tagging and ultimately, punctuation removal on the data. Datasets are then often organised into three sections: training, validation, and testing. Some of the specific models used for classification are CNN-LSTM, DT, and SVM. For instance, the

CNN-LSTM model uses convolutional neural network for feature extraction, and LSTM networks in time series analysis. These are basic measurements that are used to estimate the models' efficiency; they include accuracy, precision, recall, and F1-score. This comprehensive evaluation helps identify the most effective model for predicting customer sentiment and informs the development of robust marketing strategies.

The following steps of data flow diagram are detailed descriptions given in below:

3.1. Data Collection

In the first stage of this project, data is gathered. For this, the Amazon Product Review dataset was compiled using JSON files containing reviews found on the Amazon website. Computers, smartphones, tablets, TVs, and security cameras are all part of the collection of evaluations.

3.2. Data Preprocessing

Data pre-processing refers to the steps used to transform raw data into clean data. Due to the lack of processing, the data obtained when it is collected from several sources cannot be used for assessment purposes. In this, different steps were performed on the dataset that is described below:

- **Lowercase:** The process comprises changing all capital letters in the review text to lowercase.
- **Stop word Removal:** Some examples of stop words in a language include "the," "a," "an," "is," and "are," which are used rather often. These words were omitted from the review material since they do not provide any relevant information for the model.
- **Tokenization:** Words or tokens were broken down into smaller bits for each phrase in the review texts.
- **Part-of-Speech Tagging:** In this stage, a POS tag is assigned to each word in the sentence. For example, a verb is indicated by the tag "VB," an adjective by "AJJ," and a noun by "NN."
- **Punctuation Removal:** The review contents were edited to remove any punctuation marks.

3.3. Data Splitting

The CNN-LSTM model is divided into three parts that were consisted of 13,057 product reviews into 70% training, 10% validation, and 20% testing datasets.

3.4. Classification Models

This analysis chooses different machine learning models for depth-analysis of marketing product strategies that

3.4.1. CNN-LSTM

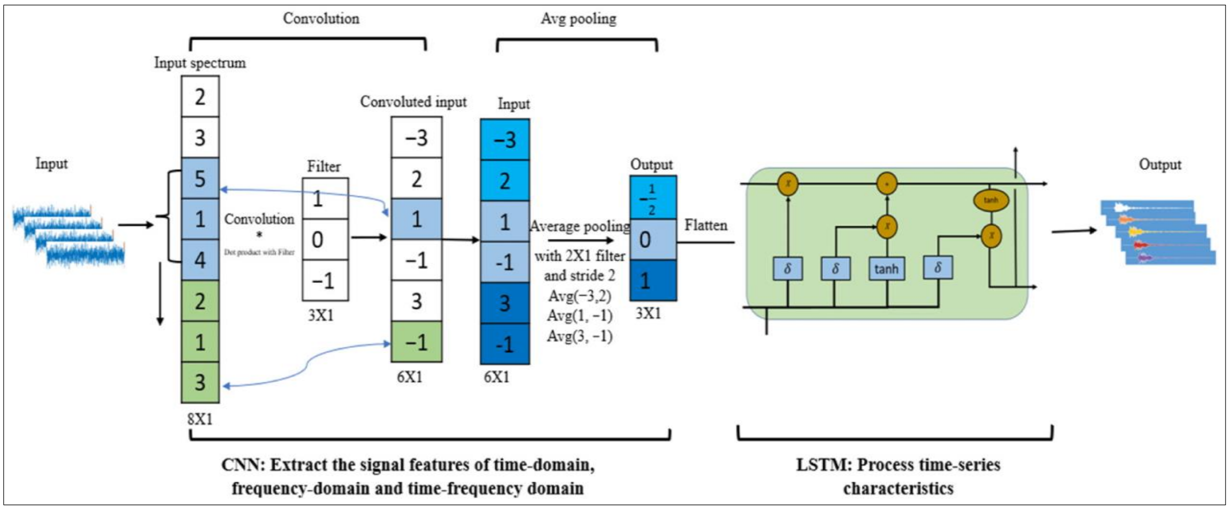

Figure 3 Flow chart of the CNN-LSTM hybrid model

Figure shows the suggested CNN-LSTM hybrid model's structure and data processing flow. A CNN layer's job is to sift through monitoring data and pull-out signal properties in a time domain, frequency domain, and time-frequency domain simultaneously. An LSTM layer was trained to analyse time series data by first putting the acquired features into a twodimensional array(17)(18). The next sections demonstrate the CNN feature extraction method and the LSTM feature processing technique. The next sections demonstrate the CNN feature extraction method and the LSTM feature processing technique. An CNN, LSTM, and CNN-LSTM models were enhanced with batch normalisation layers to standardise the outputs of every layer, therefore reducing the risks of overfitting and improving the stability of the optimisation process. Additionally, the batch normalisation layers have shown to be effective (19).

A goal of the widely used CNN technique in DL is to analyse input in several dimensions simultaneously. The two primary layers that make up a CNN are the max-pooling layer and the convolutional layer, as seen in Figure.

The input data is processed by the convolutional layer using activation and convolution processes, which in turn generate feature maps [29]. Equation 1 below shows the mathematical technique of convolution in layer l, as stated in (20):

$$C_j = f\left(\sum\nolimits_{mi\ E\ M} mi\ x\ kj + bj\right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1)$$

The convolutional layer's data input is denoted by mi, the convolutional kernel by kj, and the bias by bj in this context. We refer to the activation function as f (·).

After a convolutional layer, an average pooling layer serves to shorten a calculation time for a network and lower feature map resolution. Equation 2. below illustrates the mathematical formula for the pooling process in layer L:

$$S_j = \beta_j down\ (cj) + bk\ \ \ldots \ldots \ldots \ldots \ldots \ldots\ (2)$$

where down (·) represents an average pooling method.

Encoding long-term relationships between sequence data time steps is the LSTM layer's primary function (21). The pattern recognition data is returned by the last layer. To regulate the cell's and layer's hidden states, four parts are required: a cell candidate (g), an output gate (o), a forget gate (f), and an input gate (i) [36]. Figure 3 shows the data flow at time step t, namely the LSTM structure.

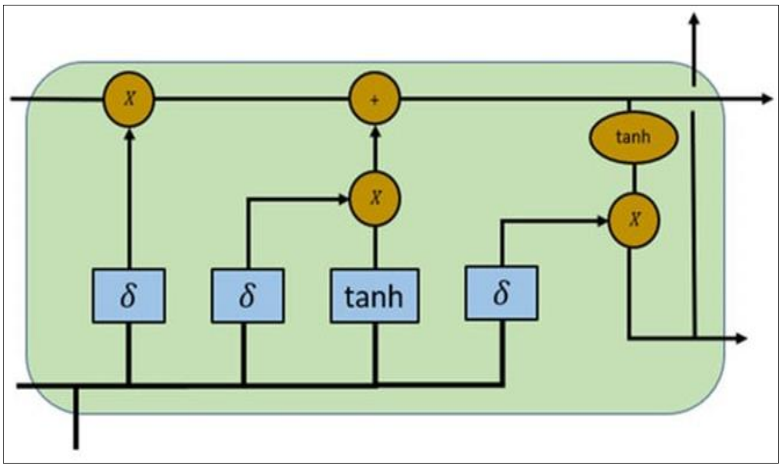

Figure 4 The LSTM structure of a cell

Equations 3 and 4 define the input gate (it) as controlling the cell state update, and the forget gate (ft) as controlling the cell state reset (forget). At the same time, the cell state added to the hidden state is controlled by the cell candidate (gt) in Equation 5 and the additional information to the cell state is shown by the output gate (ot) in equation 6 (22):

$$i_t = \sigma_g(W_i x_t + R_i h_{t-1} + b_i)\ \ \ldots \ldots \ldots \ldots \ldots \ldots (3)$$

$$f_t = \sigma_g\left(W_f x_t + R_f h_{t-1} + b_f\right)\ \ \ldots \ldots \ldots \ldots \ldots \ldots\ (4)$$

$$g_t = \sigma_c\left(W_g x_t + R_g h_{t-1} + b_g\right)\ \ \ldots \ldots \ldots \ldots \ldots \ldots (5)$$

$$o_t = \sigma_g(W_o x_t + R_o h_{t-1} + b_o) \ \dots\dots\dots\dots\dots (6)$$

A gate activation function is stated as σb, where t is the time step, W and R are the matrices representing the input and recurrent weights and bias of each element, and b is the bias of the whole thing.

ct is a condition of the cell at a current time step t, and it is specified in equation 7(22):

$$c_t = f_t \odot c_{t-1} + i_1 \odot g_t \ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(7)$$

where $\odot$ is a Hadamard product.

ht is an undisclosed condition at time step t, and it is specified in equation 8(22)

$$h_{t-1} = o_c \odot \sigma_c(c_t) \ \dots\dots\dots\dots\dots.(8)$$

where σc is the state activation function.

3.4.2. Decision Tree

Regression and classification-related issues may be solved using supervised learning techniques like decision trees. Each leaf node represents the result, the branches indicate the classification rules, and the interior nodes reflect the dataset features in this tree-structured classifier. In our implementation, we developed a decision tree classifier using tools like sci-kit learn.

3.4.3. Logistic Regression

A statistical technique called logistic regression is used to estimate the probability of an event occurring. Three separate models are often included in logistic regression: binary, multinomial, and ordinal models. Class discrimination is the goal of discriminative models, which include logistic regression. Problems with detection, classification, and prediction are common areas of use for logistic regression. The predicted values are converted to binary predictions by rounding them in our logistic regression model.

3.4.4. Support Vector Machine

SVM is used for both classification and regression. Finding a hyperplane that efficiently sorts data into distinct categories while also optimising the margin between them is its goal. We built a pipeline for text categorisation using the sci-kit-learn module as the opening stage of this strategy.

3.4.5. Model Evaluation

This is a crucial component; the suggested models were assessed employing a following metrics: F1-score, recall, accuracy, and precision. It is useful for determining which model best fits our data and for gauging the model's future performance.

3.5. Confusion Matrix

The sample's TP, FP, TN, and FN rates are shown in the confusion matrix. When assessing the CNN-LSTM model's ability to use unseen data to forecast consumer sentiment, these rates served as the basis for the computation of evaluation measures like accuracy, recall, precision, and F1-score.

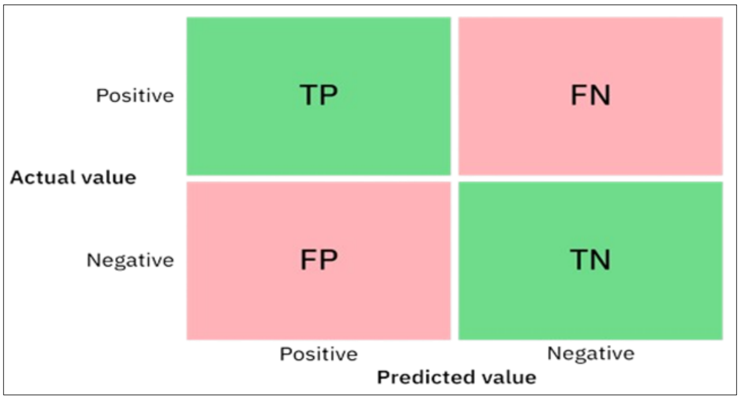

Figure 5 Representation of Confusion Matrix

- **True Positive (TP):** A number of positive records that were accurately identified is shown by TP.
- **False Positive (FP):** FP shows how many false positives were recorded from negative samples.
- **True Negative (TN):** A number of negative records that were accurately categorised is indicated by TN.
- **False Negative (FN):** The value of FN indicates the number of positive samples that were mistakenly recorded as negative.

3.5.1. Accuracy

Equation 9 shows that it is the ratio of the number of comments that were successfully categorised to the total number of comments.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad \dots\dots\dots (9)$$

3.5.2. Precision

Equation 10 states that it is the ratio of the number of positively classified statements to the fraction of those remarks that were properly categorised.

$$Precision = \frac{TP}{TP + FP} \dots\dots\dots\dots\dots\dots\dots\dots (10)$$

3.5.3. Recall

This is the proportion of correctly categorised positive comments relative to the total number of comments in that category, as illustrated in Equation 11.

$$Recall = \frac{TP}{TP + FN} \dots\dots\dots\dots\dots\dots\dots \quad (11)$$

3.5.4. F1-Score

According to Equation 12, it is the sum of the weights assigned to recall and precision.

$$F1 - Score = \frac{2 * Precision * Recall}{(Precision + Recall)} \dots\dots\dots\dots\dots\dots (12)$$

4. Result Analysis and Discussion

The comparative depth analysis of market product strategies based on ML models is provided in this section. F1-score, recall, accuracy, and precision are the four assessment measures that were used in this investigation, along with a few ML models. The following table compares many ML algorithms that are useful for in-depth product strategy analysis in the market.

4.1. Exploratory data analysis

Any study analysis must begin with exploratory data analysis. To guide targeted hypothesis testing, exploratory data analysis primarily looks for distribution, outliers, and anomalies in the data. Data visualisation, plotting, and manipulation without assumptions is an essential first stage in EDA, which follows data collection and pre-processing. This helps in evaluating the data's quality and constructs models.

Figure 6 Word Cloud of the Dataset

The word cloud, shown in Figure 6, visualises the most frequent words in the dataset, with larger words indicating higher frequency. Prominent words include "phone," "camera," "bought," "first," "work," and "great," suggesting that these terms are common in the dataset's text.

4.2. Results experiments

The experiment results of machine learning methods for marketing product strategies using confusion matrix of CNN-LSTM, model accuracy performance, and model loss performance of these models.

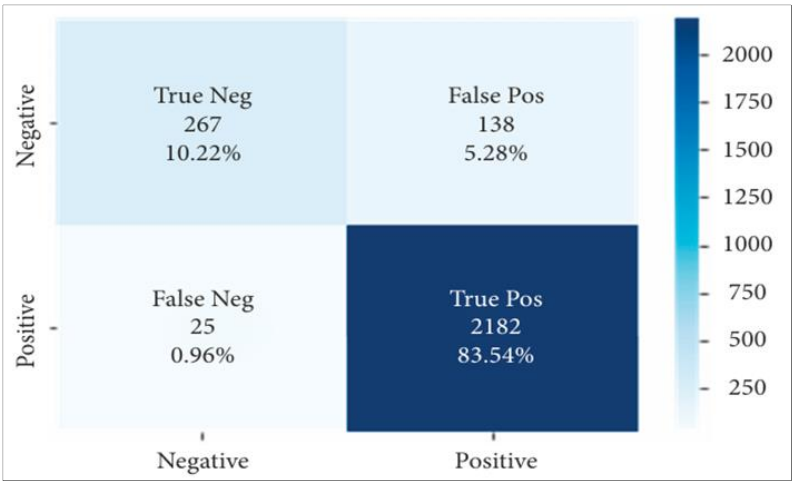

Figure 7 Confusion Matrix for CNN-LSTM model

Figure 7 displays the confusion matrix of the CNN-LSTM model, which illustrates how well it performed in a binary classification task. The matrix shows 2182 true positives (83.54%), 25 false negatives (0.96%), 138 false positives (5.28%), and 265 true negatives (10.22%). With great accuracy in forecasting positives (true positives) but with some misclassifications in both negative FP and positive (FN), these numbers show the model's capacity to properly identify negative and positive classes.

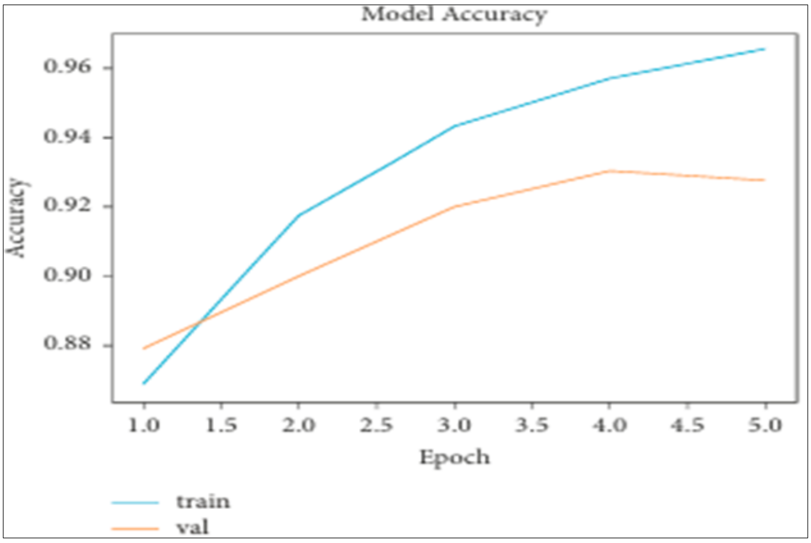

Figure 8 Model Accuracy Performance of the CNN-LSTM Model

In figure 8, a graph is shown that indicates the accuracy performance of the CNN-LSTM model throughout 5 epochs. While training, the CNN-LSTM Model improved its accuracy performance from 87.50% to 97%. As shown in the image, an accuracy performance of 94% was achieved throughout the validation phase. The training line is blue, while the validation line is orange.

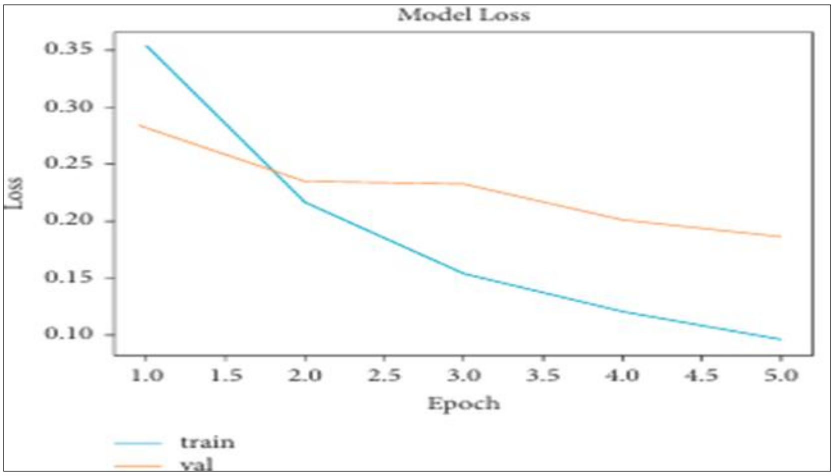

Figure 9 Model Loss Performance of the CNN-LSTM Model

The loss performance of the CNN-LSTM model for both the training and validation datasets throughout 5 epochs is depicted in Figure 9. The loss performance of the CNN-LSTM model during validation was 0.20, as seen in the figure above. Lines representing the training and validation models are blue and orange, respectively.

Table 2 Comparison between various machine learning models for depth-analysis of market product strategies

Models	Accuracy	Precision	Recall	F1-Score
CNN-LSTM	94	94	99	96.03
DT (23)	82	88.8	88.4	88.6
SVM (24)	76	71	45	51

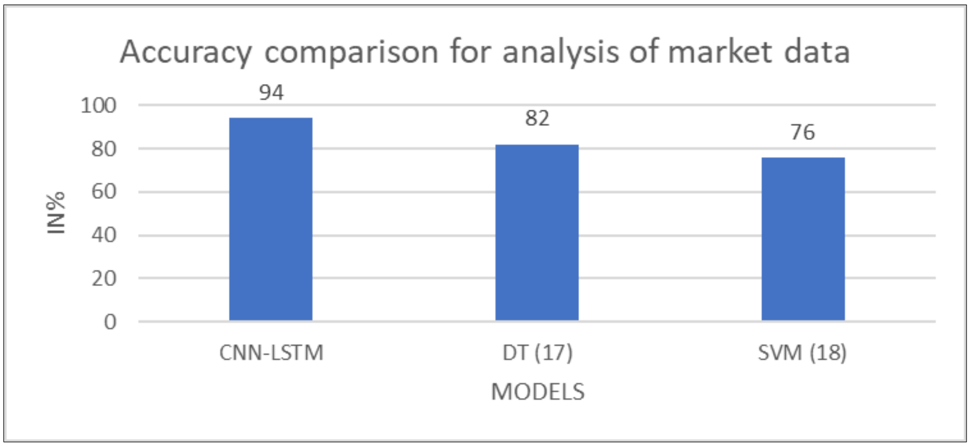

Figure 10 Bar Graph for Accuracy Comparison of Models

The above figure 10, shows the Bar Graph of Accuracy Comparison of different models. In this CNN-LSTM has the highest accuracy with 94%, and SVM has the lowest with 76%.

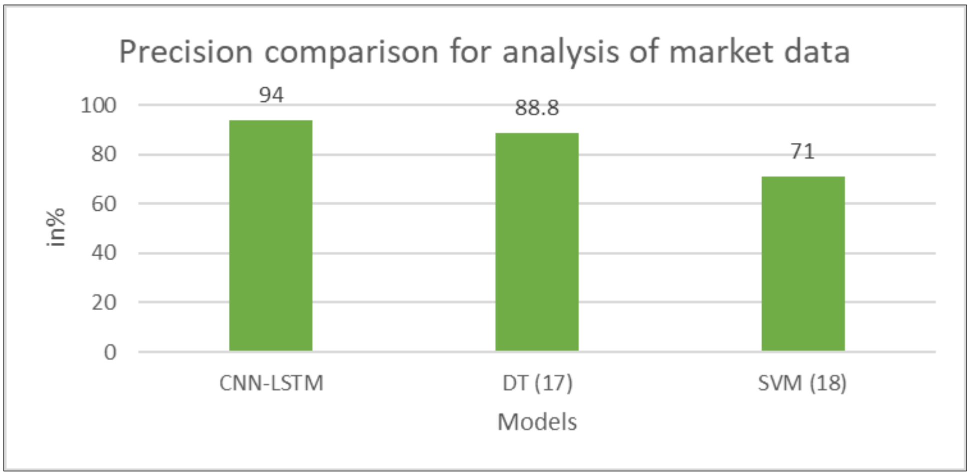

Figure 11 Precision Graph for different Comparison models

The above figure 11, shows the Precision Bar Graph for different models. In this figure, CNN-LSTM has the highest with 94%, and SVM has the lowest with 71%.

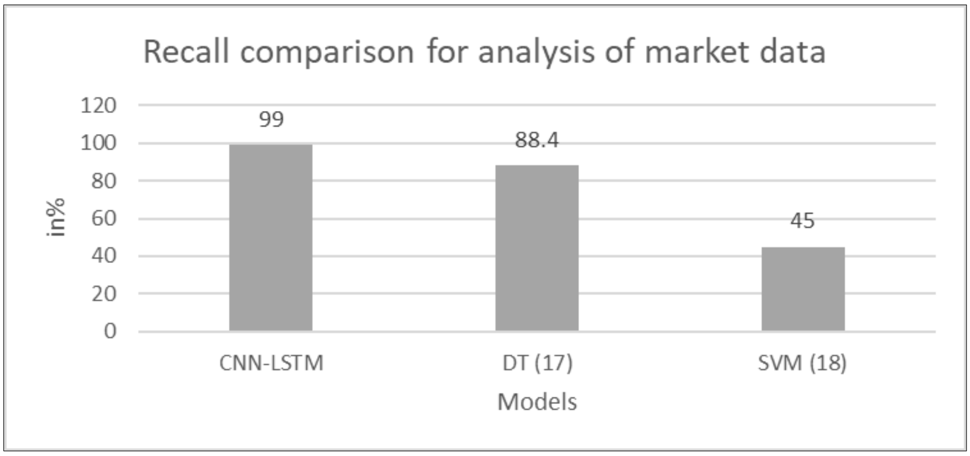

Figure 12 Comparison Bar Graph for Recall

The above figure 12, shows the Comparison Bar Graph for Recall models. In this CNN-LSTM has the highest recall with 99%, and SVM has the lowest with 45%.

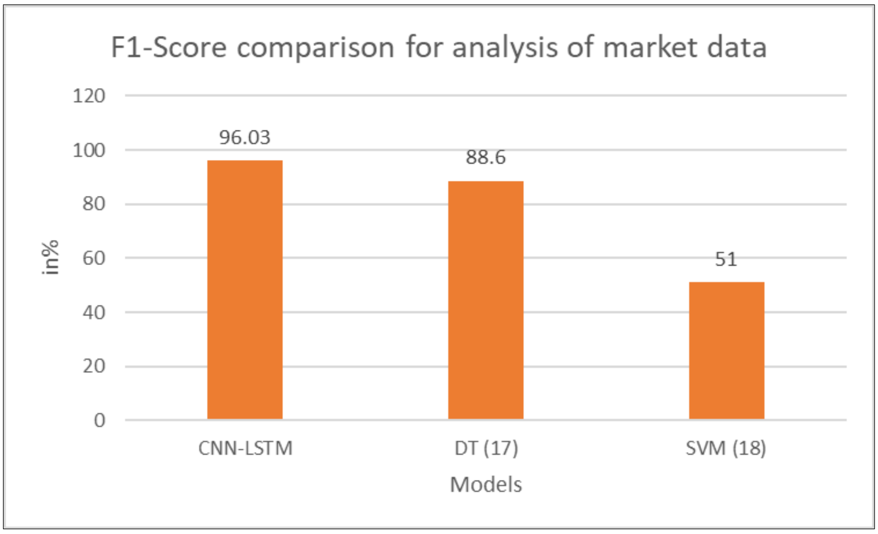

Figure 13 Comparison Bar Graph for F1-Score

The above figure 13, shows the Bar Graph Comparison for F1-Score. In this figure, CNN-LSTM has the highest F1-score with 96.03%. This indicates a highly balanced performance between precision and recall. The Decision Tree (DT) model follows with an F1-score of 88.6%, which, is still notably lower than that of the CNN-LSTM. The Support Vector Machine (SVM) model has the lowest F1-score at 51, indicating the weakest performance among the compared models, particularly in balancing precision and recall effectively.

5. Conclusion and Future Scope

In order to influence consumers' purchasing decisions, the product strategy has shown to be an important instrument. A product strategy that works for the company's new product should be carefully considered. To develop a broad selection of products that separate them from the competition, companies need to understand client preferences and the market. The competition is expanding at a rapid pace; therefore they must likewise keep up with the latest developments in this industry. This study demonstrates a comprehensive depth analysis of marketing product strategies using various machine learning models, particularly emphasising the performance evaluation of CNN-LSTM, DT, and SVM models. Among the competing models, the CNN-LSTM one performed best, with a 94% accuracy rate. In comparison, the DT, and SVM models showed progressively lower accuracy of Decision Tree with 82%, Support Vector machine with 76%, and Logistic Regression with 70%. This highlights the CNN-LSTM model's robustness in handling the complexity of marketing product strategy analysis, thereby providing valuable insights for developing more effective marketing strategies.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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