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Provide a Model Based Sentiment Analysis System for Sales Prediction in Marketing According to the AGA-LSTM Neural Network Model

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Abstract

Data is today's most powerful tool; valuable facts and information can be determined by analyzing them using appropriate techniques and algorithms. Also, the rapid increase in access to Internet technology to a large mass of people worldwide has increased the importance of analyzing data generated on the web much more than before. The preceding discussion of this research is sales forecasting in marketing, which is very important in this topic. Marketing is a tool through which people's standard of living is developed, which is done before and after the sale. This research presents a model based on a dynamic analysis system for forecasting marketing sales based on the AGA-LSTM neural network model. It is challenging to recognize emotions in natural language, even for humans, and automatic recognition makes it more complicated. This research presents a hybrid deep-learning model for accurate sentiment prediction in real-time multimodal data. In the proposed method, the work process is such that after extracting emotional data from social networks, they are pre-processed and prepared for pattern discovery. The data is evaluated in the adaptive genetic algorithm, and the pattern is discovered in the designed neural network, and this pattern is discovered after discovery. The cornerstone of sales policies is improved. The adaptive genetic algorithm was used to optimize the parameters of the LSTM model, and the model can predict the types of goods and the total volume of online retail sales. In the simulation of the proposed method, in 3000 rounds of training, an accuracy of 76 has been achieved, which is an improvement of 11% compared to the primary method.

Keyword: Sentiment Analysis System, Sales Forecasting, AGA-LSTM Neural Network Marketing, Adaptive Genetic Algorithm.

1. Introduction

Research in science and technology is mainly focused on meeting humans' ever-increasing needs and requirements for an easy life. Information technology has been at the top among such aspects with reasonable throughput in terms of success in meeting those human needs. To be more accurate and correct, the development of web technology in recent years has been nothing but a miracle for active audiences who observe it from a close distance. Moreover, the number of users directly benefiting from it has reflected the graph of the necessity of such technological development in the life of an ordinary person. In short, web technology has already established itself as an irreplaceable reality of human civilization. Social media, news portals, online shopping sites, and educational applications are examples of some important application areas of the web. Meanwhile, online marketing and business intelligence are one of significant and valuable applications of web development. Also, social media's influence in online marketing and business intelligence is inevitable (Khatiwada, A., Kadariya, P., Agrahari, S., & Dhakal, R., 2019, December).

.All people are related to marketing in their life. Marketing is a tool through which people's standard of living is developed. Many people think marketing is the same as sales, but marketing activities are done before and after the sale. Marketing practically includes many activities such as marketing research, product development, distribution, pricing, and personal selling, and the goal is to satisfy buyers' needs and achieve organizational goals simultaneously. Marketing management analyzes, plans, implements, and controls planned activities to create, build and maintain exchanges and mutually beneficial relationships with the desired markets to achieve organizational goals. Achieving this goal depends on a systematic and specified analysis of the target market's needs, desires, conclusions, and preferences and their intermediaries as a basis for practical decisions about goods, price, communication, and distribution. The old concept of marketing management started with the company's existing products and considered marketing as the act of selling and encouraging buyers to acquire literacy through increasing sales. The new concept starts with the current and potential buyers of the company and seeks profit by creating customer satisfaction and accomplishes this by organizing a complete and extensive marketing program at the company level. The strategic concept of marketing has changed the focus of marketing management to strategic participation and stabilization of the company's position through communication between sellers and buyers in the value chain to create value for customers.

In today's era, when the concepts of communication, competition, customer orientation, and business are inextricably linked, electronic marketing, as an element of existing businesses and trade, plays a central role in maintaining and surviving businesses through attracting. It plays a role in keeping customers, introducing and introducing products, and creating motivation to feel the need to buy because marketing elements are considered one of the well-known tools for expanding and penetrating the market and stealing the ball of superiority from commercial competitors. Since marketing is an intermediary between the producer (supplier, provider) and the consumer and plays a vital role in the prosperity of business goals of commercial institutions, on the other hand, the prosperity of sales (products or services) lead to the expansion of production and increase in the level of national income. On the other hand, economic, commercial, and social institutions support new media to expand the sphere of influence and attract audiences and customers for their goods, products, services, ideas, and opinions. Therefore, electronic marketing in the form of marketing activities through the global Internet network is considered and used as the most extensive and influential communication network. Many individuals and companies of small and large and different capitals in The internet network platform are busy trading goods and services. The effect of e-marketing on the sale of products is very widely used.

The main goal of this research (based on the article (Khatiwada, A., Kadariya, P., Agrahari, S., & Dhakal, R., 2019, December)) is to develop a system to analyze the sentiments of people in the social network on a product released in the market. Product business owners can get an idea of how the product performs in the current market conditions and the strengths and weaknesses shown by the general public. Using this information, they can make the necessary adjustments to capture better and influence business value. A method has been developed that includes data pre-processing and training, data chunking, filtering, data analysis, and finally, feeding the segmented data to The model for specifying emotional values, To fulfill this research goal. That sentiment analysis of textual data can be done using deep learning (Khatiwada, A., Kadariya, P., Agrahari, S., & Dhakal, R., 2019, December). As a result of this research answers the question: Is it possible to provide a model based on the sentiment analysis system for sales forecasting in marketing based on the AGA-LSTM neural network model?

2. Related Works

Marketers have a significant asset if they effectively target social networks' influentials. They can advertise products or services with free items or discounts to spread positive opinions to other consumers (i.e., word-of-mouth). However, the primary research on choosing the best influentials to target is single-objective and mainly focused on maximizing sales revenue. In this paper, we propose a multi-objective approach to the influence maximization problem to increase the revenue of viral marketing campaigns while reducing costs. Using local social network metrics to locate influentials, we apply two evolutionary multi-objective optimization algorithms, NSGA-II and MOEA/D, a multi-objective adaptation of a single-objective genetic algorithm and a greedy algorithm. Our proposal uses a realistic agent-based market framework to evaluate the fitness of the chromosomes by simulating viral campaigns. The framework generates a set of non-dominated solutions that allow marketers to consider multiple targeting options in a single run. The algorithms are evaluated on five network topologies and an entire data-generated social network, showing that both MOEA/D and NSGA-II outperform the single-objective and greedy approaches. More interestingly, we show a clear correlation between the algorithms' performance and the diffusion features of the social networks (Robles, J. F., Chica, M., & Cordon, O., 2020).

This research is the addition to making online business more user-friendly, interactive, and output-oriented. The online marketing and sales of the products increase significantly if the opinion of the public for the product is analyzed intermittently. As the trend today is that people immediately update their response to the products they face on social media, the developed system provides the platform for large-scale producers to inspect how consumers respond to their products. The concept of Big Data Analysis is used for data collection, pre-processing, and data analysis. A model is obtained by training the available Data using Deep Learning, which is used to determine the sentiment values of the collected comments. Finally, the Python libraries visualize the Sentiment analysis results and other obtained information (Khatiwada, A., Kadariya, P., Agrahari, S., & Dhakal, R., 2019, December).

Under the vigorous development of China's market economy, the marketing mix is constantly updated, promoting the overall development of various industries. Social media marketing has formed a solid theoretical and practical foundation, especially with the continuous updating and iteration of Internet technology and the improvement of people's requirements for experience, and we must find ways to optimize the methods of social media marketing. This study mainly introduces several optimization methods of social media marketing based on deep neural networks and advanced algorithms, and the experiments of gradient-based back-propagation algorithm and adaptive Adam's optimization algorithm show that the proposed optimization algorithm can quickly achieve the optimal global state based on the combination of back-propagation algorithm and Adam's optimization algorithm. Accuracy of marketing is essential, so we introduce a scheme of how to market accurately, and the scheme is effective. Firstly, the FCE model is constructed by a three-layer back-propagation neural network, and then, the data input layer is designed to achieve the effect of the model (Bian, Q., 2021).

Huang et al. (2021)." A strategic framework for artificial intelligence in marketing." The authors develop a three-stage framework for strategic marketing planning, incorporating multiple artificial intelligence (AI) benefits: mechanical AI for automating repetitive marketing functions and activities, thinking AI for processing data to arrive at decisions, and feeling AI for analyzing interactions and human emotions. This framework outlines how AI can be used for marketing research, strategy (segmentation, targeting, positioning, STP), and actions. At the marketing research stage, mechanical AI can be used for data collection, thinking AI for market analysis, and feeling AI for customer understanding. At the marketing strategy (STP) stage, mechanical AI can be used for segmentation (segment recognition), thinking AI for targeting (segment recommendation), and feeling AI for positioning (segment resonance). At the marketing action stage, mechanical AI can be used for standardization, thinking AI for personalization, and feeling AI for renationalization. We apply this framework to various areas of marketing, organized by marketing 4Ps/4Cs, to illustrate the strategic use of AI (Huang, M. H., & Rust, R. T., 2021).

Artificial intelligence (AI) is (re)shaping strategy, activities, interactions, and relationships in business, specifically marketing. Ethical controversies are the drawback of the substantial opportunities AI systems and applications (will) provide in marketing. Building on the literature on AI ethics, the authors systematically scrutinize the ethical challenges of deploying AI in marketing from a multi-stakeholder perspective. By revealing interdependencies and tensions between ethical principles, the authors shed light on the applicability of a purely principled, deontological approach to AI ethics in marketing. To reconcile some of these tensions and account for the AI-for-social-good perspective, the authors suggest how AI in marketing can be leveraged to promote societal and environmental well-being (Hermann, E., 2022).

Marketing mix modeling (MMM) is an essential technique in marketing measurement to define the effectiveness and efficiency of marketing investment. MMM is a complex combination of various statistical models and data transformation functions. Traditional MMM is subject to analyst bias and is slow and expensive. This disclosure describes automated techniques that reduce analyst bias in MMM and make the model-building process fast, flexible, and inexpensive. The techniques described in this disclosure overcome analyst bias through a multi-objective hyperparameter optimization that is achieved by using an evolutionary algorithm (Zhou, G., Sentana, L., Skokan, I., & Prada, A., 2021).

The genetic algorithm belongs to a group of evolutionary algorithms that find inspiration in Darwin's theory of maintaining the best species. It is based on only three operations: selections, crossover, and mutations. The application space is found in all areas that require optimization by finding the values of the variables that optimize the target function. Each genetic algorithm, therefore, uses a fitness function to choose the best crossover units from the population in the next generation. The optimal structure of sales assortment is a theoretical and pragmatic challenge to the sales function in every market-oriented organizational system. In this paper, optimizing the sales assortment structure determines the share of individual products in a group of products sold in a particular market. There is a hypothesis that the structure of the sales assortment can be optimized using the genetic algorithm. The paper developed a software solution in C# to verify the central hypothesis, and the solution is open to new extensions and demonstrates a satisfying application power (Markić, B., 2019).

With the development of e-commerce, online retail is becoming larger and larger. Sales volume prediction faces the challenges of various categories and changeable customer demands. Based on this, this paper proposes an online retail prediction model based on AGA-LSTM neural network. In the process of building an LSTM neural network, the adaptive genetic algorithm (AGA) is used to optimize the network parameters such as time step, hidden layer number, and training times to improve the prediction accuracy of the model, and it is used to forecast the types of goods and the total sales volume. The results on the Online Retail II dataset in UCI show that the prediction accuracy of the AGA-LSTM model is greatly enhanced compared with the traditional LSTM model, which verifies the effectiveness of this algorithm (Chen, K., 2020, October).

3. The Proposed Method

Considering that most reviewed methods are based on traditional machine learning or neural network model to predict the sales volume of goods, ignore the algorithm's shortcomings, and can no longer meet the prediction and analysis of complex online sales data. This chapter proposes an online retail forecasting model based on the methodology, results, and analysis framework developed by tracking the response of Facebook and Twitter users for a specific product and determining the success rate of the product in the market using the AGALSTM neural network.

This model uses Adaptive Genetic Algorithm (AGA) to optimize the network parameters of the LSTM neural network, such as time step, number of hidden layers, and training times, to overcome the shortcomings of LSTM itself, such as high gradient vanishing. The training cost of this method can improve the model's prediction accuracy, which can be used to predict the total online retail sales volume.

This research aims to develop a system to analyze people's sentiments in social media towards a product launched in the market. Product owners can view this idea of how the product is performing in the current market conditions and its strengths and weaknesses by others. Using this information, they can make the necessary adjustments to improve it and increase the value of the business. The flowchart of the proposed method is shown in Figure 1 and is briefly summarized in the following steps:

- In the proposed method, they are pre-processed and prepared for pattern discovery after extracting emotional data from social networks.
- Further, the data is valued in the adaptive genetic algorithm. The pattern is discovered in the designed neural network, and this pattern is improved after discovering the cornerstone of sales policies.
- Adaptive Genetic Algorithm is used to optimize LSTM model parameters, and the model can predict the types of goods and the total volume of online retail sales, a method was developed that includes data pre-processing and training using deep learning to achieve the goal of this research, data removal, data filtering and analysis, and finally, feeding the removed data to the AGALSTM model to determine sentiment values. Data visualization is done after providing emotional value for all comments by the AGALSTM model. Graphical displays were used to indicate whether the level of customer satisfaction was poor, neutral, or excellent. In addition, a polarity curve against comment ID is also generated to visualize the identity of the customer who

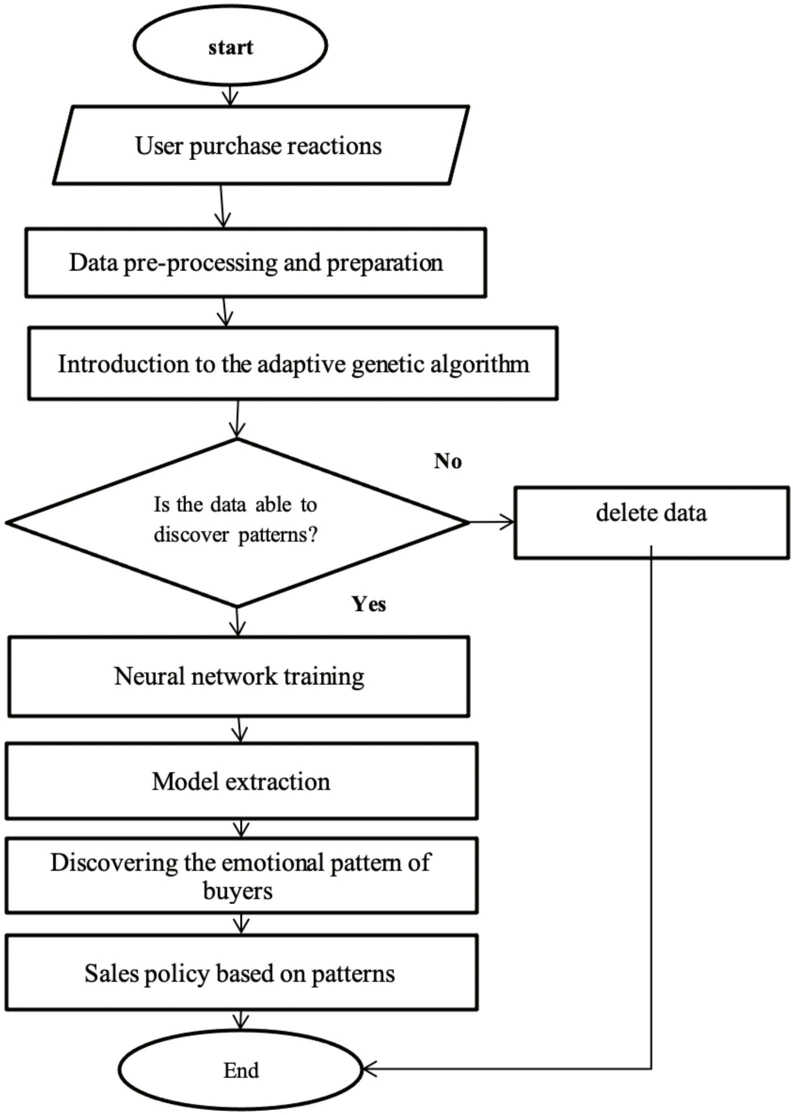

Fig. 1: Flowchart of the proposed method

submitted such comments (Chen, K., 2020, October).

Data pre-processing and training using deep learning: The first step in this research was to use the dataset to train a model for sentiment analysis. In the proposed method, we use the seq-to-seq model, a type of RNN, to develop a test generation model for language translations, automatic response systems, news headline generation, and speech-to-text conversion. However, since this was not required in this section, the proposed method only uses the LSTM model to generate sentiment values, which is a

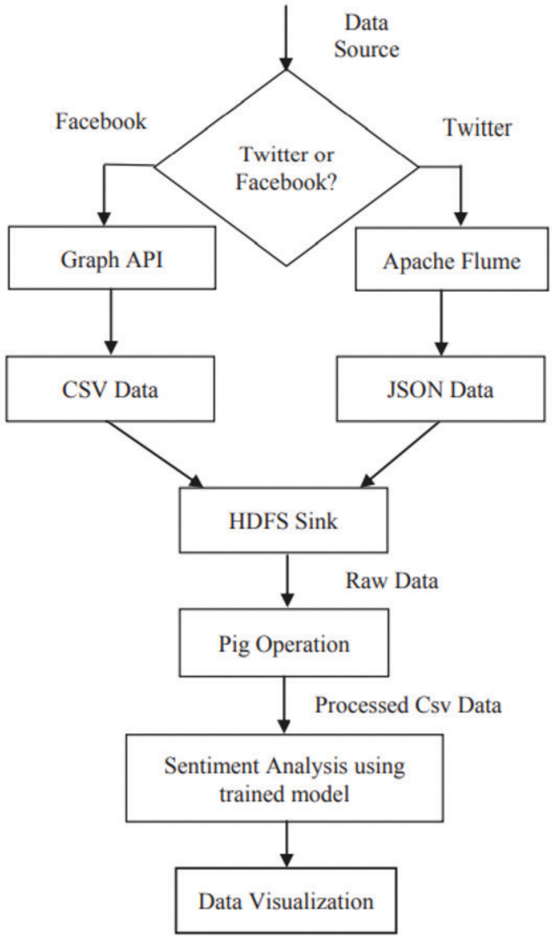

Fig. 2: Sequence of Operation of Developed System

kind of deep learning network composed of different layers (Khatiwada, A., Kadariya, P., Agrahari, S., & Dhakal, R., 2019, December).

Filtering and data analysis: The comments obtained from both sources have multiple contexts that may not be relevant to the proposed method. Since the data span is preserved from before deletion, the only field required was user comments on the product. For this purpose, we used the MapReduce task. The Latin pig script performed the necessary operations with the data set. Finally, another data set was obtained after the pig operation, containing only comments with sentiments to be analyzed. This operation is shown in Figure 2. Therefore, data from both sources were merged into a single file containing only Facebook and Twitter comments, in descending "creation time" order to ensure that comment IDs were not random. The final file contains the cleared comments for analysis, stored in the appropriate location in local memory to be later detected by the script for visualization work.

The last and most crucial step in this research is determining the sentiment of the filtered comments. For this process, the Panda library was used to import the file containing filtered comments, and then the Python script was written to feed all the comment data from the file to the training model row-by-row using looping codes. The outcome of the process was the array with the comment numbers as the key and the sentiment values between 0 to 10 as the values. Now, the sentiment value in this array was plotted using the matplotlib library of Python with the number of comments in the y-axis and the sentiment classes in the x-axis, clearly illustrating the public opinions towards the product. Also, another graphical representation was generated, which showed the comment ID vs. comment sentiment graph. As the latest comments have less value of ID than lately made comments, this graph helps to illustrate how the public response has been affected by the time (Khatiwada, A., Kadariya, P., Agrahari, S., & Dhakal, R., 2019, December). ADAPTIVE GENETIC ALGORITHM AND LSTM NEURAL Network: Swarm intelligence algorithms have been widely used to optimize the parameters of neural network models. Among them, the adaptive genetic algorithm(AGA) (Chen, K., 2020, October) is an optimized genetic algorithm that was proposed in 1994. Unlike the standard genetic algorithm, the AGA algorithm can protect the excellent individuals in the population as much as possible, inhibit the occurrence of premature phenomena, and jump out of the local optimum, and the optimization performance is better. Therefore, we use the adaptive genetic algorithm to construct the optimization network, adjust and optimize the parameters of the LSTM neural network, such as the time step, the number of hidden layers, and the training times, obtaining the LSTM neural network with the optimal parameters, and its prediction performance is better than other) (Chen, K., 2020, October).

ONLINE RETAIL PREDICTION MODEL BASED ON AGA-LSTM NEURAL NETWORK: This paper makes full use of the ability of the adaptive genetic algorithm to optimize parameters of the LSTM neural network, such as the time step, the number of hidden layers and training times, to make the parameters more optimal and effectively improve the time series prediction ability of the model. Then, an online retail prediction model based on AGALSTM neural network is constructed and applied to the daily online sales forecast) (Chen, K., 2020, October).

The Process of AGA-LSTM Online Retail Prediction Model: rail network, the adaptive genetic algorithm maps the three parameter values of the LSTM neural network (time step parameter Ts, hidden layer number N, data training times Epochs) so that each chromosome becomes the parameters combination of the whole LSTM model. In training the LSTM model, it iterates continuously to find the optimal parameters set of the model. The AGA-LSTM model is constructed to predict the total sales of online reta (Chen, K., 2020, October).

In the AGA-LSTM neural network-based online retail forecasting model, the mean square error (MSE) between the predicted value and the actual value of the LSTM neural network is designed as the fitting of the chromosomes. The smaller the value, the more reasonable the parameter value of the LSTM neural network and the better the prediction performance of the model (Chen, K., 2020, October).

Set MSE_ias the mean square error of chromosome i, the calculation formula is shown in (1), num is the number of test sets, Pij is the prediction result of the LSTM neural network corresponding to chromosome (the set of parameters), and Aij is the actual value of sample) (Chen, K., 2020, October). The Process of AGA-LSTM Online Retail Prediction Model In the online retail prediction model based on the AGA-LSTM neural network, the adaptive genetic algorithm maps the three parameter values of the LSTM neural network (time step parameter Ts, hidden layer number N, data training times Epochs), so that each chromosome becomes the parameters combination of the whole LSTM model. In training the LSTM model, it iterates continuously to find the optimal parameters set of the model. The AGA-LSTM model is constructed to predict

$$\mathrm{MSE_i} = \frac{1}{\mathrm{mm}} \sum_{\mathrm{j=1}}^{\mathrm{mm}} (\mathrm{P_{ij}} - \mathrm{A_{ij}})^2 \tag{1}$$

the total sales of online retail (Chen, K., 2020, October).

4. Simulation and Results

Social media has enabled information mobilization, where users can post and share a variety of multimodal texts in the social environment without having much knowledge about web client-server architecture and network topology. Removing communication and demographic barriers is a communication channel, social listening, and feedback tool for stakeholder engagement and collaboration. Nevertheless, large organizations and businesses are eager to develop applications supporting automated text analysis, and extracting meaningful information from high-variety multivariate data is critical. In this chapter, the simulation of the proposed method is discussed using MATLAB.

Dataset Selection: The online retail II data set is selected as the experimental data set from the UCI database, a transnational data set. It records all online transaction order information of online retailers in the UK from December 1, 2010, to December 9, 2011, including customer number, order number, total type of goods, total sales volume, and unit price. The company mainly sells gifts and has many wholesaler customers. This paper mainly forecasts the daily sales volume and total types of goods in the company's online retail. The features of this collection are as follows:

Invoice number: invoice number. Nominal A 6-digit integral number that is uniquely assigned to each transaction. If this code starts with the letter "c," it indicates cancellation.

StockCode: product code (items). Nominal A 5-digit integral number that is uniquely assigned to each product.

Description: Name of the product (item). Nominal

Amount: Amounts of each product (item) per transaction. Numerical

InvoiceDate: date and time of the invoice. Numerical The day and time the transaction was created.

UnitPrice: unit price. Numerical Product price in sterling (£).

Customer ID: Customer number. Nominal A 5-digit integral number that is uniquely assigned to each customer.

Country: Name of nominal country. The name of the country where the customer resides.

Sentiment analysis is the central part of this research. The validity of collected opinions and other data used to predict the future of the product must be fundamentally well-interpreted and valid. For this purpose, the developed framework was tested for accuracy to determine the sentiment of the book 'Fantastic Beast' and the Bollywood movie 'Sanju.' The data collection was done before the publication of

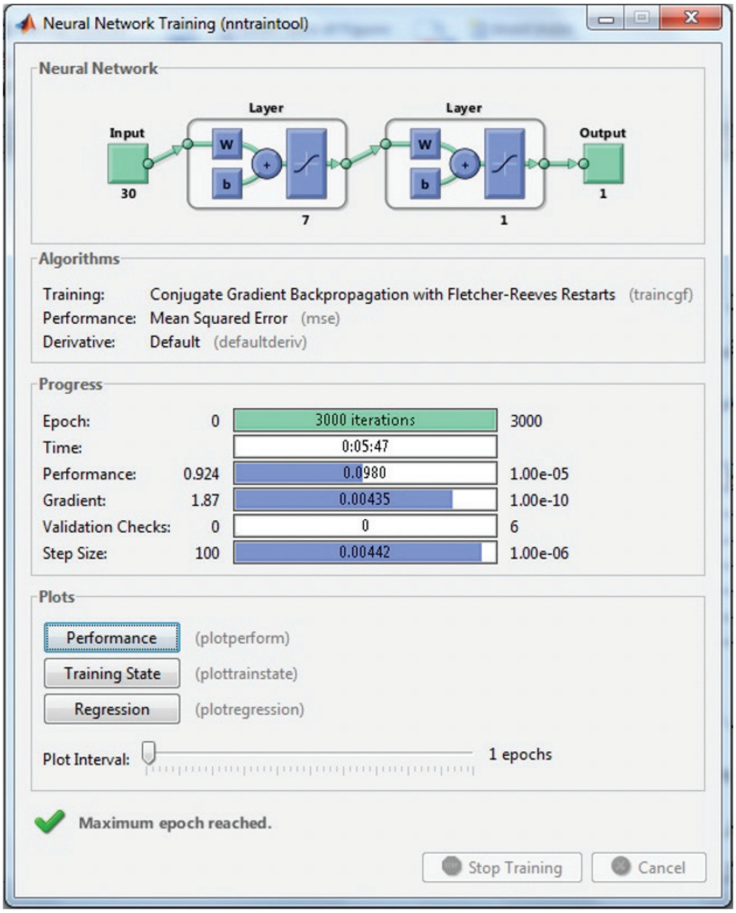

Fig. 3: Simulation environment of the proposed method

these two cases. A representation of the simulation environment is shown in Figure 3.

Data was removed from Twitter and the film's official Facebook page to determine the sentiment of the said film. A similar phenomenon happened in the book. After filtering for the movie and book below, the total number of comments shows emotional details that can be used to make decisions to improve product

Table 1: Classification of sentiment classes

SN.	Sentiment Class	Sentiment Value Range
1	Very Poor	0-1.25
2	Poor (25 %)	1.25-2.5
3	Bad (40%)	2.5-3.75
4	Neutral	3.75-6.25
5	Sound (60%)	6.25-7.5
6	Very Good (75%)	7.5-8.75
7	Excellent	8.75-10.0

performance. The emotional values obtained between 0 and 10 are shown in Table 1 and are based on the number of opinions clustered in a specific class according to Figures 4 and Figure 5.

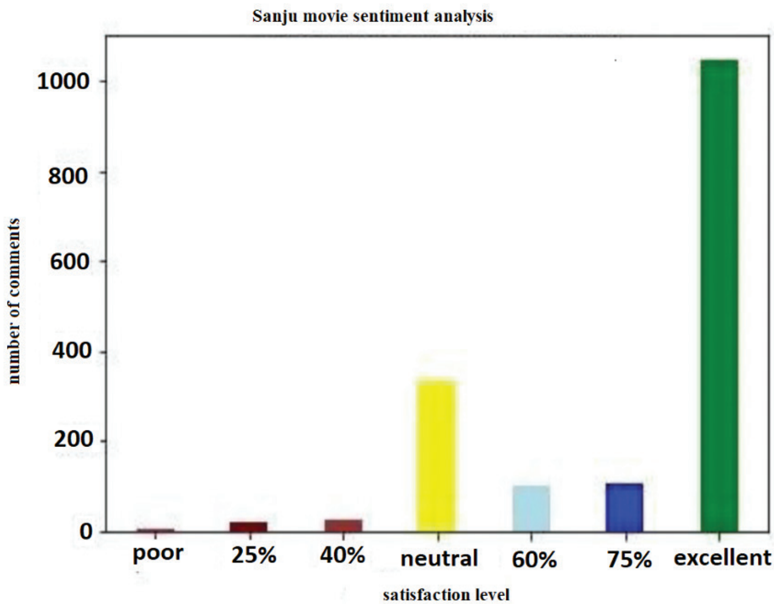

Fig. 4: Graph indicating the number of reviews in different sentiment classes for Sanju Movie

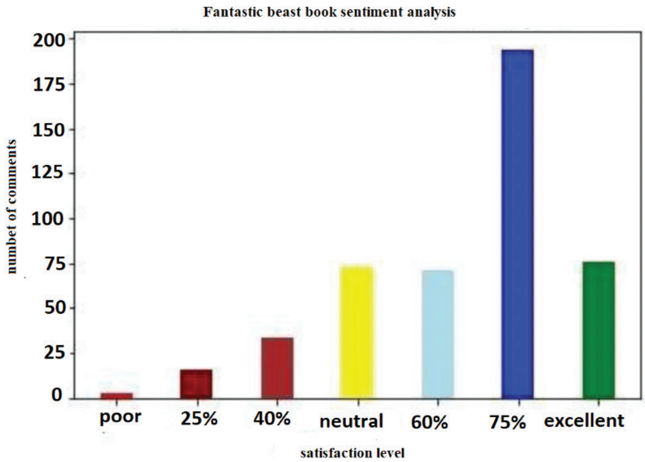

Fig. 5: Graph indicating the number of reviews in different sentiment classes for Fantastic Beast Book

Also, to determine the negative and positive response time, the polarity diagram was drawn against the ID of comments according to Figure 6 and Figure 7. Here, the smallest Id value represents the last comment used to refer to it. Purpose of Analysis: This chart shows the polarity of comments as it moves from left to right, showing recent sentiment to older comments.

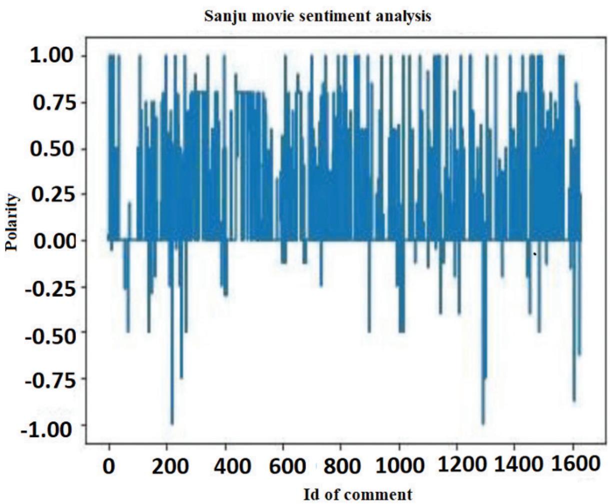

Fig. 6: Polarity vs. Id of Comment graph. Range redefined between -1 to +1 to indicate the negative and positive sentiment for Sanju Movie.

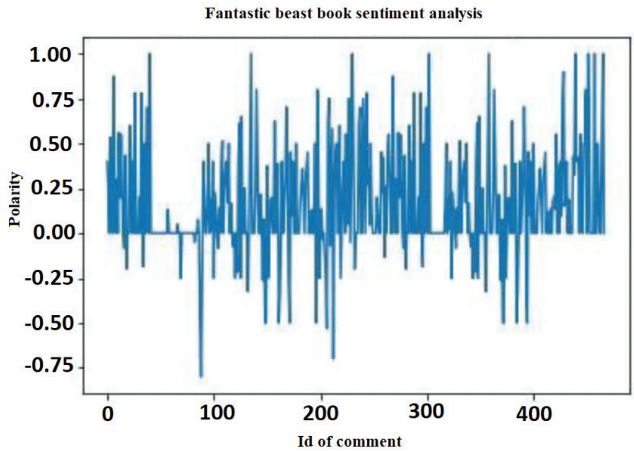

Fig. 7: Polarity vs. Id of Comment graph. Range redefined between -1 to +1 to indicate the negative and positive sentiment for Fantastic Beast Book

100 opinion samples were randomly selected, each of which was considered positive, to analyze the accuracy or inaccuracy of the output from the sentiment analysis process negative and neutral after the analysis by the system. These comments were arbitrarily chosen for both the book and the movie. These individual comments were then manually analyzed, and their sentiments were determined. Finally, the results of these two analyses were compared, and the accuracy criterion of the used logic was interpreted, described in detail below.

Positive Sentiment Analysis

Total number of sample comments = 100

Total Number of Correct Results = 84

Total Number of Incorrect Results = 16

So, Error % = ((100-84) / 100) * 100 % = 16 %

Hence, % Accuracy = 100 – 16 = 84 %

Therefore, the system works well when analyzing positive sentiment comments. Therefore, we can rely on the output the analyzer provides whenever it is positive.

Negative Sentiment Analysis

Total Number of taken Samples = 100

Total Number of correct Results = 72

Total Number of incorrect Results = 28

So, % Error = ((100-78)/100) * 100 = 28 %

Hence, % Accuracy = 100 – 28 = 72 %

From the above results, it can be confirmed that the system can manage and partition negative comments correctly. However, it was found that the system needed help to correctly determine the sentiment of comments in languages other than English.

Neutral Sentiment Analysis

Total number of taken samples = 100

Total number of correct results =62

Total number of incorrect results = 38

So, % Error = ((100 - 62) / 100) * 100 = 38 %

Hence, % Accuracy = 100 – 38 = 62 %

After this analysis, it was found that the system can have difficulty determining neutral comments. Although it accurately marked neutral comments as neutral, there were problems analyzing positive and negative non-English language comments and those with special characters. It was also found that such comments were marked as neutral by the framework. However, it does not provide inflated predictions because the neutral output does not hinder the prediction scheme much.

Overall Sentiment Analysis

Total number of taken samples = 100 + 100 + 100 = 300

Total number of correct result =84 + 72 + 62 = 218

Total number of incorrect result = 16 + 28 + 38 = 82

So, % Error = (82 / 300) * 100 = 27.33%

Hence, % Accuracy = 100 – 27.33 = 72.66 %

Overall, the above result suggests that even if there is a significant accuracy problem in the case of neutral sentiment analysis, this system can still be effectively used to analyze sentiment in comments that users or individuals respond to. They give or use the relevant products. Services. Since neutral opinions are not considered positive or negative at any moment, public opinion is not determined by applying the developed system. In time series forecasting, if the state is forecast n times later, the forecast is n-step. When n = 1, it is single-stage forecasting; n> 1 is multi-stage forecasting. Based on BP, LSTM, and AGA-LSTM deep neural networks, this experiment developed online retail forecasting models to forecast a British online retailer's one-day, five-day, and future sales volume. The prediction accuracy of each model is compared to verify the performance of the AGALSTM model. After data pre-processing, we take 70% of the data set as the training set, 20% as the validation set, and 10% as the test set

$$\mathrm{MSE} = \sum_{j=1}^{n_t}(y_i' - y_i)^2/n_t \tag{2}$$

The evaluation index of the model is set as the mean square error MSE from equation (2). where nt is the number of test sets, y_i' is the prediction result, y_i is the actual value of the test sample. The lower the sum of the leveling errors, the better the performance of the model and the smaller the prediction error. It should be noted that for the MSE value under multi-stage prediction, both the actual and predicted MSE values are the average values in the future. Then they are calculated according to the formula (2).

Table.2. The mse value of three models under different prediction steps. (Total daily sales volume)

	The prediction model		
Prediction step	BP	LSTM	AGA-LSTM

One-step	39.6	26.8	18.7
Five-step	50.7	32.3	25.6
Five-step	62.3	48.5	37.3
Average MSE value	50.9	35.9	27.2

Table 2 shows the MSE values of three online retail forecasting models based on BP, LSTM, and AGA-LSTM under single-step, 5-step, and 10-step forecasting of total daily sales volume. Table 2 shows that the MSE values of the BP model are the largest in single-stage, 5-stage, and 10-stage forecasting, followed by the LSTM model. The MSE values of the online retail forecasting model based on the AGA-LSTM neural network are the lowest, which indicates that the prediction error of this model is the smallest, and the prediction of the total sales volume is the closest to the actual value, which validates the model.

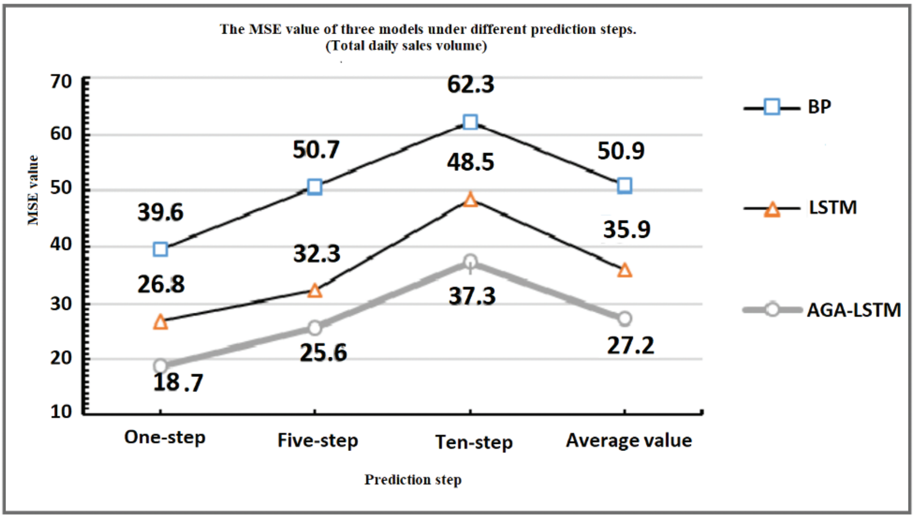

Fig. 8: The MSE value of three models under different prediction steps. (Total daily sales volume)

Average values of three models under single-step, 5-step, and 10-step prediction. Regarding the three prediction stages, the average MSE of the LSTM model is 29.5% lower than the BP model, and the AGA-LSTM model is 24.2% lower than the traditional LSTM model. It proves that the AGA algorithm can improve the parameter setting of the LSTM neural network to a certain extent, and it can significantly improve the performance of time series forecasting and realize the forecasting of the total daily sales volume. Table 3 shows the MSE values of three models based on BP, LSTM, and AGA-LSTM under single-stage, 5-stage, and 10-stage forecasting of all types of goods. Figure 9 shows the trend of MSE value and the average value of the total commodity types predicted by the three models outlined in Table 3-4.

Table 3. The mse value of three models under different prediction steps. (Total types of goods)

	The prediction model		
Prediction step	BP	LSTM	AGA-LSTM
One-step	13.5	9.6	5.7
Five-step	19.1	21.3	10.3
Five-step	28.9	25.9	16.4
Average MSE value	20.5	18.9	10.8

It can be seen from Table 3 and Figure 9 that the MSE values of the AGA-SLTM model presented in this article have the lowest values in each forecast stage. The average MSE value of the AGALSTM model is 47.3% lower than the BP model and 42.8% lower than the LSTM model. This shows that the AGA-LSTM model has the highest prediction accuracy for all types of goods, and the algorithm's performance is better than the other two models. However, with the increase of prediction steps, the prediction accuracy of the three models decreased.

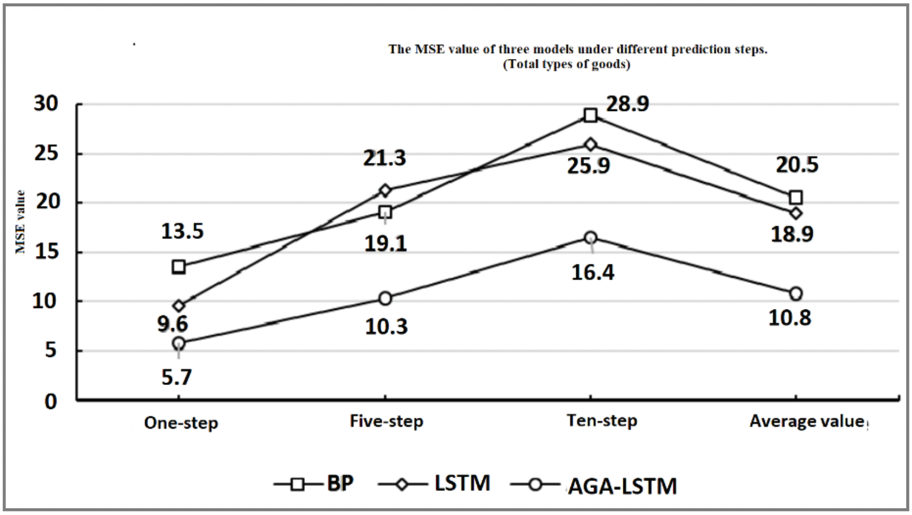

Fig. 9: The MSE value of three models under different prediction steps. (Total types of goods)

Also, as shown in Figure 10, the proposed method has achieved an accuracy of 76 in 3000 rounds of training, which is an improvement of 11% compared to the primary method, which shows the optimality of the proposed method.

Conclusion

Recognizing emotions in natural language is difficult even for humans, making automatic recognition even more complex. This research presents a hybrid deep-

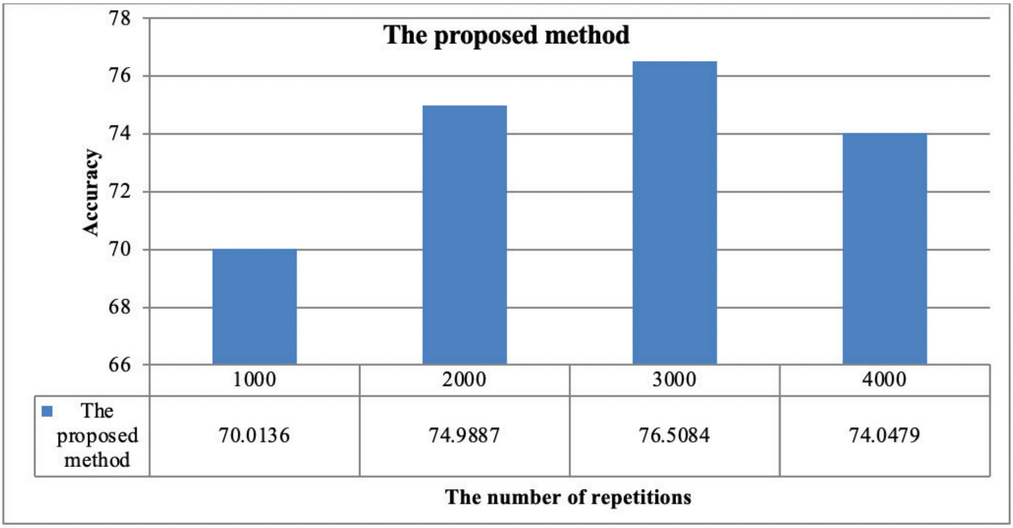

Fig. 10: Display of the output of the proposed method in different iteration rounds

learning model for accurate sentiment prediction in real-time multimodal data. It leverages the strengths of deep learning networks in combination with machine learning to deal with two specific semiotic systems, namely textual (written text) and visual (still images), and their combination into online content using decision-level multimodal integration. A model was proposed to provide a model based on a dynamic analysis system for forecasting sales in marketing to deal with In this article. In the proposed method, they are pre-processed and prepared for pattern discovery after extracting emotional data from social networks. Further, the data are valued in the adaptive genetic algorithm, and the pattern is discovered in the designed neural network, and this pattern is the cornerstone of sales policies for They improve. Moreover, the simulation of the proposed method achieved 77% accuracy, which showed a 6% improvement compared to the primary method.

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