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Research Article

Analysis of Fine Food Reviews Using Intelligent Computing Model

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ABSTRACT

automated overall review score based on text descriptions. This would provide companies a quick and accurate way to measure customer satisfaction without needing manual inspection and analysis. We used the LSTM (Long Short Term Memory), RNN (Recurrent Neural Network), and GRU (Gated Recurrent Unit) designs, three widely used recurrent neural network (RNN) architectures, to do this. Tasks requiring sequence modeling, such as natural language processing, are ideally suited for these systems. The "Amazon Fine Food Reviews" dataset that we acquired from Kaggle was first preprocessed. In order to do this, the dataset needed to be cleaned up by having the comments' special characters and punctuation removed. To create a fair and understandable dataset, we additionally chose a subset of the data depending on the duration of the reviews. In addition, we used word clouds for exploratory data analysis to understand the distribution of the most common terms. Next, we utilized the preprocessed dataset to train our LSTM, RNN, and GRU models. Based on the input text descriptions, these models were trained to predict the total review score. In order to reduce the loss value and increase accuracy, the model parameters were optimized throughout the training phase. We evaluated the effectiveness of our models utilizing the testing group. The findings demonstrated that our model produced effectively a loss value of 0.2 for the testing group. This suggests that our algorithm can pretty accurately and effectively estimate the overall review score based on the text descriptions.This approach may be applied practically to automate the generation of an overall evaluation score in the food sector. The model may provide an impartial evaluation of customer happiness by examining the text descriptions that consumers have submitted. Based on user input, it can assist companies in monitoring and enhancing the quality of their goods or services. Overall, our study shows that LSTM, RNN, and GRU models are capable of accurately predicting review scores based on text descriptions. The model's accuracy and loss values suggest that it may be useful in automating review analysis and measuring customer happiness.

Keywords: automated review score, text descriptions, recurrent neural network (RNN), LSTM (Long Short Term Memory), GRU (Gated Recurrent Unit) ,preprocessing, Amazon Fine Food Reviews dataset

1. INTRODUCTION:

In today's digital era, with the progress of science and information technology, the world has become a global village [1]. Social media platforms are extensively used by more than 50% of the world's population for entertainment, information, marketing, and various online activities [2]. This widespread usage of social media generates a vast amount of data in the form of tweets, posts, and customer reviews related to different products. However, this data often contains redundancy and inconsistency, which can

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hinder the overall performance of systems and consume significant memory space. Additionally, these data often exhibit polarity issues, making it challenging for companies to understand their customers' needs, emotions, and behaviors [3]. To overcome these challenges, sentiment analysis, also known as opinion mining, plays a vital role in classifying text and detecting polarity. Sentiment analysis helps in identifying ambiguity in language and opinions, revealing how individuals feel about a particular topic [4]. The choice of words and expressive mood while writing often involves personal opinions and emotions. Several algorithms have been developed to analyze, anticipate, and assess sentiments from text data, such as product or customer evaluations. However, sentiment analysis faces difficulties related to spam and fake data, domain dependence, negation, overhead of natural language processing, bi polar terms, and a vast lexicon [5]. To address these challenges and improve the effectiveness and efficiency of the data mining process, this research focuses on sentiment analysis of user evaluations using deep learning [6]. Deep learning methods, known for their successes in various domains, are employed for sentiment analysis through classification. The objective is to extract subjective information from text, particularly consumer reviews, and accurately categorize them into positive and negative sentiments. The dataset used in this study comprises Amazon cell and accessory product reviews obtained from the Snap dataset [7]. The proposed method aims to enhance the sentiment analysis process in web based environments and achieve superior results with high confidence and minimal computational complexity [8]. In this study, various preprocessing tasks, including data cleaning, normalization, hashtag and punctuation removal, text conversion to lowercase, and tokenization, are examined to improve the classification of consumer reviews. The preprocessing steps are described in detail in Section . The major contributions of this work lie in data selection, preprocessing, and classification[9]. Firstly, the impact of different preprocessing activities on consumer reviews is investigated, and benchmark datasets used by other researchers are employed. Secondly, a suitable feature encoding method is selected to represent the numeric features of customer reviews for classification and analysis. This ensures that each review is converted into a fixed length vector, considering the varying sizes of text in the reviews. The use of an appropriate embedding layer is emphasized for accurate sentiment classification. Finally, deep learning based LSTM models with different layers and parameters are utilized for classifying data and identifying the exact sentiment. These models demonstrate comparable or improved results compared to previous approaches, considering metrics such as accuracy, specificity, precision, and F1 measures. The rest of the paper is structured as follows: Section 2 provides a summarized literature review on sentiment analysis. Section 3 outlines the proposed methodology for the classification of consumer reviews. Section 4 presents the experimental results of three models, namely Model 1, Model 2, and Model 3, which differ in terms of network architecture and parameters. The final section concludes the paper, highlighting the contributions of this work and key findings[10].

2. BACKGROUND THEORETIC

In this section introduce the Literature work, Fine Food Reviews, and deep learning about LSTM, RNN, GRU.

2.1 Literature Work:

The most popular topic of research in the last several years is sentiment analysis, which is now being actively studied by researcher . **Kartikay**, et al. [11], conducted sentiment analysis on Amazon Fine Food Reviews dataset. Logistic regression achieved the highest accuracy among the machine learning algorithms used. The results showed positive sentiments were prevalent in the reviews. LSTM, a deep learning model, achieved an impressive accuracy of 92.1%. The study emphasized the usefulness of sentiment analysis in understanding public opinion. **Sinha** [12] , discusses the importance of product

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reviews in e commerce websites like Amazon and proposes a model for sentiment analysis to classify reviews as positive, negative, or neutral. The authors use data analysis techniques and classification algorithms to analyze Amazon food reviews data and determine the sentiment of the reviews. The study aims to improve the accuracy of the existing review system and differentiate between fake and real reviews. The dataset used consists of over 500,000 food reviews from Amazon. This work provides an overview of the methodology, including data collection, preprocessing, selection of relevant features, and the application of various classification algorithms such as Naive Bayes, Support Vector Machine, and K Nearest Neighbor. The results and accuracies of the classification algorithms are analyzed using tools like Scikit Learn and Jupyter Notebook. **Zhao** [13], develops a BERT based model to predict review scores using text descriptions from the "Amazon Fine Food Reviews" dataset. Data cleaning involves removing missing, non English, and duplicate comments. Punctuation is dropped, time variable is converted, and pre 2010 comments are removed. The dataset is balanced through resampling and split into training, validation, and testing sets. A word cloud identifies keywords. The fine tuned BERT model achieves an accuracy of 0.7982 and loss of 0.5433. The paper discusses using the model to generate scores for food businesses based on text reviews. **Hafiz Muhammad, et al** [14],focuses on sentiment analysis of Amazon Fine Food reviews using Big Data analytics. Traditional systems are unable to process the growing amount of data, so the authors utilize Apache Spark, a data processing system, for analysis. Three machine learning techniques, namely Linear SVC, Logistic Regression, and Naïve Bayes, are applied using Spark's MLlib library. The results show that Linear SVC performs more efficiently than the other methods, achieving over 80% accuracy. The study highlights the importance of sentiment analysis for online reviews and the potential of Big Data analytics in handling large datasets.

2.2 Fine Food Reviews

Fine Food Reviews is a reputable online platform that specializes in providing comprehensive and reliable reviews of various culinary experiences. As a trusted source for food enthusiasts, Fine Food Reviews offers detailed assessments of restaurants, cafes, food trucks, and other dining establishments, helping consumers make informed choices when it comes to their dining preferences[15]. The platform takes pleasure in keeping a staff of knowledgeable food critics and reviewers that have a wealth of expertise and experience in the culinary industry. These experts visit and assess a variety of restaurants, taking into account the food's quality, presentation, service, atmosphere, and overall eating experience. From casual diners to foodies and tourists looking for extraordinary culinary adventures, Fine Food Reviews wants to serve a varied audience. The portal assists readers in finding new dining establishments, locating hidden treasures, and avoiding possible disappointments by offering thorough and objective evaluations. Additionally to restaurant evaluations, Additionally, Fine Food Reviews may include articles on a variety of topics related to the food industry, such as chef interviews, cooking advice, and recipe suggestions[16]. With this multidimensional approach, readers can investigate different facets of the culinary world, increase their knowledge, and develop a greater appreciation for excellent eating. Whatever you're searching for at a dining establishment—a romantic date place, a family friendly eatery, or an adventurous culinary journey—Fine Food Reviews aims to be a trustworthy and useful resource for anybody seeking exceptional meals. [17].

2.3 Deep learning

Machine learning's area of deep learning focuses on teaching artificial neural networks to understand and extrapolate meaning from large amounts of complicated data. It has transformed a number of industries, including speech recognition, computer vision, and natural language processing. Long Short

Journal of Information Systems Engineering and Management
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Term Memory (LSTM) and Gated Recurrent Unit (GRU) are two examples of recurrent neural networks (RNNs) within deep learning that are frequently employed for processing sequential data[18].

- Long Short Term Memory (LSTM): LSTM is a type of RNN architecture that addresses the vanishing gradient problem, which can occur when training traditional RNNs on long sequences. It consists of memory cells and gates that allow information to flow selectively, retaining and updating relevant information over time. LSTM networks are designed to capture long term dependencies in sequential data, making them well suited for tasks like language translation, speech recognition, and sentiment analysis [19].
- Recurrent Neural Networks (RNN): RNNs are a class of neural networks designed to process sequential data by maintaining an internal state or memory. They operate on sequences of inputs, processing one element at a time while retaining information from previous steps. This makes RNNs effective for tasks such as text generation, handwriting recognition, and time series analysis. However, traditional RNNs suffer from the vanishing/exploding gradient problem, limiting their ability to capture long term dependencies [20].
- Gated Recurrent Unit (GRU): GRU is another variant of RNNs that addresses the vanishing/exploding gradient problem while maintaining simpler architecture compared to LSTM. It incorporates gating mechanisms similar to LSTM but with fewer gates, making it computationally efficient. GRUs are widely used in applications such as speech recognition, natural language understanding, and video analysis[21].

By enabling the modeling of sequential data with long term dependencies, LSTM and GRU have both contributed significantly to the advancement of deep learning. They have greatly enhanced the performance of several tasks requiring sequential data and have developed into crucial tools in the fields of machine translation, speech recognition, and natural language processing[22].

3. DATASET:

The dataset comprises of fine cuisine ratings from Amazon that span more than ten years and include over 500,000 reviews as of October 2012. It contains data on the product and the user, as well as reviews in plain language. The information is taken from the database's related sqlite file, which contains the "Reviews" SQLite table. The collection includes reviews from a range of Amazon categories and offers insightful information about consumer tastes and product opinions. The dataset is well maintained and documented, making it a trustworthy resource for education, analysis, and other uses. A word cloud representation is also presented[23].

Table1: The dataset of fine foods from Amazon description

Columns name	Description
Id:	a distinguishing number for every review.
ProductId:	a special code for the item under inspection.
UserId:	a special code that may be used to identify the reviewer.
ProfileName:	The user's profile name.
HelpfulnessNumerator:	how many people thought the review was useful.
HelpfulnessDenominator:	the percentage of users that responded positively or negatively to the review.
Score:	The product's score, which ranges from 1 to 5.
Time:	the review's time stamp.

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Summary:	a succinct synopsis of the review.
Text:	The full text of the review.

4. PROPOSED WORK

The Text Rank algorithm is the foundation of the suggested approach for extracting significant evaluations from Amazon fine food reviews and producing a summary of customer impression for a particular product. Three models—LSTM, RNN, and GRU—were put forth in the present work to evaluate food evaluations using data from Amazon. Data cleaning, solving missing values, removing language and duplicate values, removing punctuation and special characters, and scoring distribution analysis were some of the preparatory stages that the data through. To balance the dataset, resampling techniques have been used. Here is a thorough explanation of each action:

step 1: Data Cleaning: The dataset's missing values were found and handled correctly. This can entail removing occurrences with missing data or imputed values.

step 2: Language and Duplicated Values: We looked for instances of non English content and duplicate reviews in the dataset. Reviews that were not in English were eliminated, and duplicate reviews were either eliminated or handled in accordance with the criteria.

step 3: Punctuation and Special Characters: Special letters and punctuation were taken out of the text data. This process aids in data standardization and noise reduction.

step 4: Score Distribution: To comprehend the data balance and find any potential biases, the distribution of review scores was examined. The assessment and interpretation of the model depend on these data.

step 5: Resampling: Techniques of resampling were used to resolve any class imbalance in the dataset. Class imbalance is when one class has a disproportionately high or low number of instances compared to the other classes. The majority class may be undersampled, the minority class may be oversampled, or a combination of the two may be used in resampling.

step 6: Model Analysis: Groups for Training, Validation, and Testing: The dataset was divided into groups for training, validation, and testing. The validation set is used for hyperparameter tweaking and model selection, the training set is used to train the models, and the testing set is used to assess the final performance of the chosen model.

step 7: Words Cloud: To illustrate the most common terms in the dataset, a word cloud was created. This offers comprehension of the important phrases used in the reviews and can aid in comprehending the terminology used in a certain subject.

step 8: LSTM, RNN, GRU Models: For the analysis of the meal evaluations, three models—LSTM, RNN, and GRU—were put into practice. Tasks involving sequence analysis frequently employ these models. Each model has a unique architecture and set of learning capabilities, making it appropriate for various sorts of data and issue scenarios. These processes—including data pretreatment, resampling, and model analysis—are all included in the suggested approach. Utilizing LSTM, RNN, and GRU models, you may efficiently assess meal evaluations by following this technique.

A sequence-to-sequence model's model LSTM architecture is represented by what is given:

step 1: Embedding Layer: Apply an embedding layer to create dense vectors with defined sizes out of the input sequences. The layer creates embedded outputs using encoder inputs. It has a 100-em embedding dimension.

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/ **Research Article**

step 2: Encoder LSTM 1: Define the encoder's initial LSTM layer.. It is configured to return sequences and states. The LSTM layer takes the embedded inputs and generates outputs, as well as the hidden and cell states (state_h1, state_c1).

step 3: Encoder LSTM 2: Add a second LSTM layer to the encoder, which also returns sequences and states. It takes the outputs from the previous LSTM layer (encoder_output1) and produces new outputs and states (encoder_output2, state_h2, state_c2).

step 4: Encoder LSTM 3: Include a third LSTM layer in the encoder, which returns sequences and states. It takes the outputs from the previous LSTM layer (encoder_output2) and generates final outputs and states (encoder_outputs, state_h, state_c).

step 5: Decoder Inputs: Create an input layer for the decoder, representing the input sequence for the decoder model. The shape of the input tensor is (None,), allowing variable length sequences.

step 6: Embedding Layer for Decoder Inputs: Apply an embedding layer specifically for the decoder inputs. This layer converts the decoder inputs into embedded representations.

step 7: Decoder LSTM: Define an LSTM layer for the decoder, configured to return sequences and states. It takes the embedded decoder inputs and the states from the encoder LSTM (state_h, state_c) as initial states. The layer produces outputs, as well as the forward and backward states (decoder_outputs, decoder_fwd_state, decoder_back_state).

step 8: Attention Layer: Add an attention layer to incorporate attention mechanism into the model. The attention layer takes the encoder outputs (encoder_outputs) and decoder outputs (decoder_outputs) and computes attention weights and attention output (attn_out, attn_states).

step 9: Concatenate Layer: Concatenate the decoder LSTM outputs (decoder_outputs) with the attention output (attn_out) along the last axis. This layer combines the information from the decoder LSTM and attention mechanism.

step 10: Dense Layer: Apply a time distributed dense layer to transform the concatenated outputs into the final output shape. The dense layer applies a softmax activation function to produce probabilities for each element in the output sequence.

step 11: Define the Model: Create a Keras Model object by specifying the input and output layers. The inputs are the encoder inputs and decoder inputs, and the output is the decoder outputs. This model represents the complete architecture.

step 12: Model Summary: Display the summary of the model, which provides information about the layers, output shapes, and the number of parameters in the model.

The total number of parameters in the model is 5,011,070, all of which are trainable. It is important to ensure that the code snippet is executed within a complete script or notebook environment, as there might be additional code required for data preparation, training, and evaluation of the model. The RNN Model Define the architecture of the RNN model. Choose the number of hidden layers and the number of units in each layer such as LSTM .if necessary, based on the performance on the validation set.

5. RESULT AND DISCUSSION:

This section provides a discussion of the experimental results. Several deep learning techniques are used to evaluate the selected datasets, including several models based on the LSTM classifier for sentiment classification and evaluation. The dataset contains information on food reviews from Amazon, including the following columns: index, Id, HelpfulnessNumerator, HelpfulnessDenominator, Score, and Time and statistical measures as shown in table 2

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/ **Research Article**

Table 2: statistical measure fine foods from Amazon of dataset

index	Id	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
count	16243.0	16242.0	16242.0	16242.0	16242.0
mean	8122.0	1.5636005418	2.0467922669621967	4.1590321	12953441
std	4689.094	5.223676169576	5.929612157923727	1.31668167	46739199.9
min	1.0	0.0	0.0	1.0	961718400.
25%	4061.5	0.0	0.0	4.0	127191600
50%	8122.0	0.0	1.0	5.0	130775040
75%	12182.5	2.0	2.0	5.0	133030080
max	16243.0	202.0	219.0	5.0	135120960

Preprocessing stage The dataset is preprocessed before training the models in order to provide the training models the best input possible. The next stages, commonly referred to as the "data wrangling stage," are crucial for cleaning up data. First, all the duplicated and null values are found and eliminated from the text. Second, eliminate extraneous information from text input that might interfere with classifier performance, such as non-alphabetic letters, numerals, special characters, and punctuation marks.. As shown in figure 1

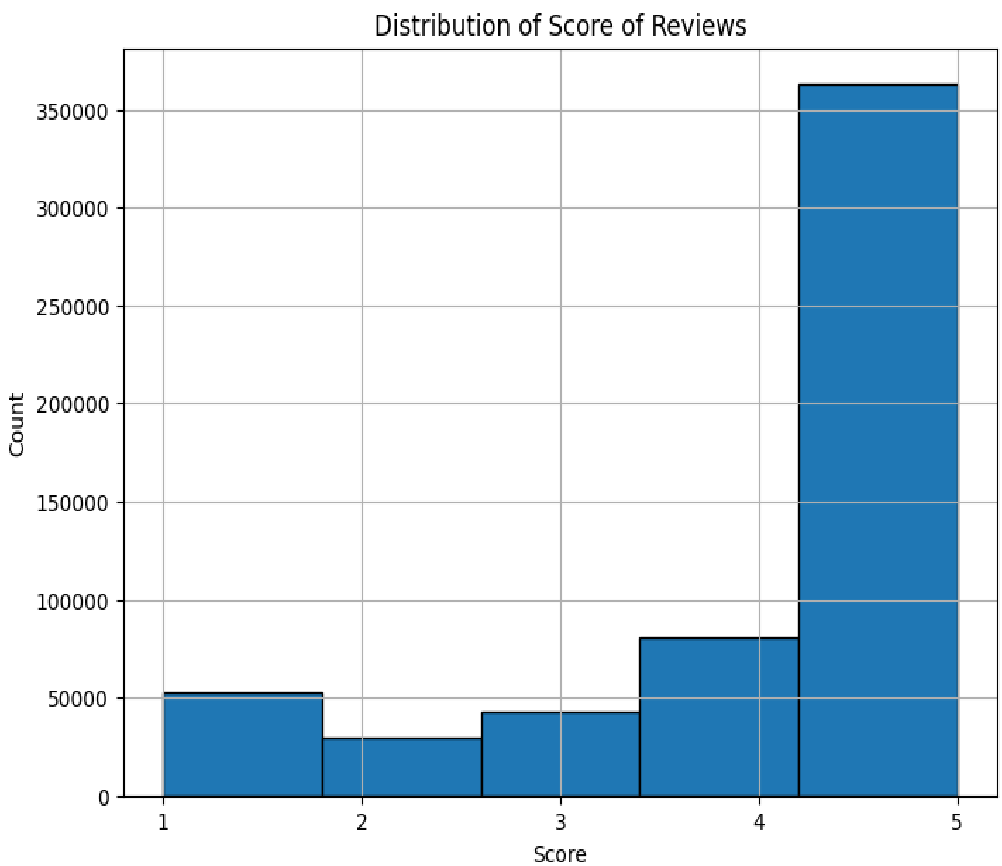

Figure 1: Distribution of Score of Reviews

Journal of Information Systems Engineering and Management
2025, 10(39s)
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https://www.jisem-journal.com/ **Research Article**

For this, make a new column called "label" that has a value of 0 or 1 depending on the helpfulness attributes, as shown in figure 2.

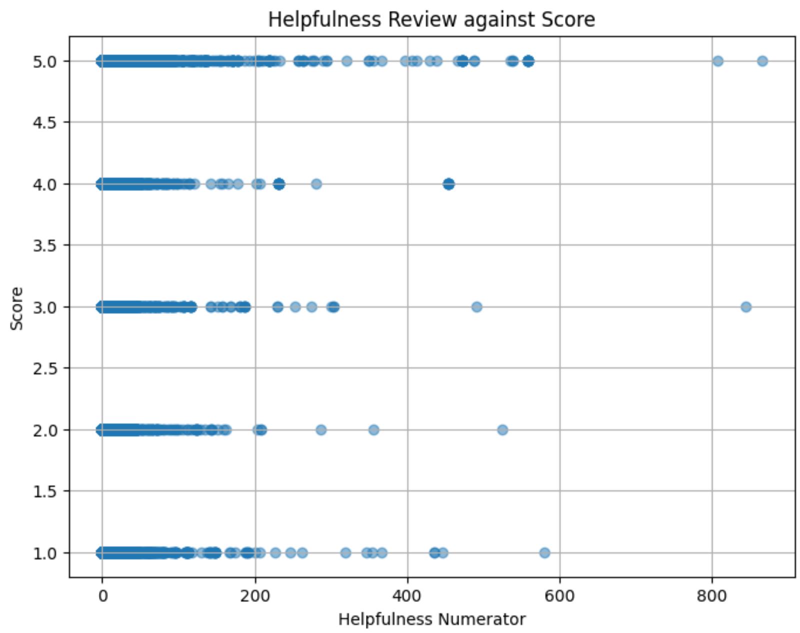

Figure2 : Review of helpfulness versus score

The next step is to tokenize the preprocessed text according to available space and eliminate stop words, which are common words and have little meaning in sentences (such as the preposition and conjunction in table 3.

Table.3: Preprocessing tokenization and stop words removal Preprocessing

Preprocessing	Sample Comment
Without tokenizing	yesterday i ordered food from kfc the food was not not cooked properly the taste of the food was very bad it was the 2nd time i faced the same problem'
After tokenizing	yesterday', 'i', 'ordered', 'food', 'from', 'kfc', 'the', 'food', 'was', 'not', 'not', 'cooked', 'properly', 'the', 'taste', 'of', 'the', 'food', 'was', 'very', 'bad', 'it', 'was', 'the', '2nd', 'time', 'i', 'faced', 'the', 'same', 'problem'
Before stop words	yesterday', 'i', 'ordered', 'food', 'from', 'kfc', 'the', 'food', 'was', 'not', 'not', 'cooked', 'properly', 'the', 'taste', 'of', 'the', 'food', 'was', 'very', 'bad', 'it', 'was', 'the', '2nd', 'time', 'i', 'faced', 'the', 'same', 'problem'
After stop words	taste', 'ordered', 'faced', 'time', 'problem', 'bad', 'properly', 'cooked', 'yesterday', 'food', 'kfc', '2nd'

Journal of Information Systems Engineering and Management
2025, 10(39s)
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https://www.jisem-journal.com/ **Research Article**

sample remarks Without tokenizing, "Yesterday I ordered food from KFC, but it wasn't cooked properly, and the taste was awful." It was the second time I encountered the identical issue. After tokenizing "yesterday," "i," "ordered," "food," "from," "KFC," "the," "food," "was," "not," "not," "cooked," "properly," "the," "taste," "of," "the," "was," "very," "bad," "it," "was," "the," "2nd," "time," "i," "faced," "the," "same," "problem," Following the stop phrases "taste," "ordered," "faced," "time," "problem," "bad," "properly," "cooked," "yesterday," "food," "KFC," and "2nd,"

The model training process consisted of 22 epochs. The initial loss value was 3.0112, which gradually decreased over the epochs. The validation loss also decreased from 2.7238 in the first epoch to 2.0448 in the last epoch. The training and validation losses indicate the performance of the model, with lower values indicating better performance. Early stopping was applied after the 22nd epoch, suggesting that the model's performance was no longer improving significantly. The training process took an average of 167 seconds per epoch, with a total training time of approximately 61 minutes.

Table 4: The training process of Training Loss , Validation Loss of models LSTM, RNN, GRU

Epoch	LSTM		RNN		GRU	
	Training Loss	Validation Loss	Training Loss	Validation Loss	Training Loss	Validation Loss
1	3.0112	2.7238	3.97608853	2.88141308	3.98179278	3.68096694
2	2.6947	2.6359	3.65958853	2.79351308	3.66529278	3.59306694
3	2.5949	2.5173	3.55978853	2.67491308	3.56549278	3.47446694
4	2.5068	2.4664	3.47168853	2.62401308	3.47739278	3.42356694
5	2.4459	2.4413	3.41078853	2.59891308	3.41649278	3.39846694
6	2.3882	2.3771	3.35308853	2.53471308	3.35879278	3.33426694
7	2.3227	2.3035	3.28758853	2.46111308	3.29329278	3.26066694
8	2.2675	2.2682	3.23238853	2.42581308	3.23809278	3.22536694
9	2.2227	2.2213	3.18758853	2.37891308	3.19329278	3.17846694
10	2.1854	2.2063	3.15028853	2.36391308	3.15599278	3.16346694
11	2.1502	2.1893	3.11508853	2.34691308	3.12079278	3.14646694
12	2.1204	2.1907	3.08528853	2.34831308	3.090992782	3.147866948
13	2.0914	2.1459	3.05628853	2.30351308	3.06199278	3.10306694
14	2.0648	2.1336	3.02968853	2.29121308	3.03539278	3.09076694
15	2.0368	2.1184	3.00168853	2.27601308	3.00739278	3.07556694
16	2.0095	2.1121	2.97438853	2.26971308	2.98009278	3.06926694
17	1.9818	2.0964	2.94668853	2.25401308	2.95239278	3.05356694
18	1.9559	2.0812	2.92078853	2.23881308	2.92649278	3.03836694
19	1.9296	2.0638	2.89448853	2.22141308	2.90019278	3.02096694
20	1.9049	2.0441	2.86978853	2.20171308	2.87549278	3.00126694
21	1.8803	2.0553	2.84518853	2.21291308	2.85089278	3.01246694
22	1.858	2.0448	2.82288853	2.20241308	2.82859278	3.00196694

Then plot (as shown in figure 4) the training and validation loss values during the model training process. which contains the recorded loss values. By monitoring the loss values, can gain insights into the

Journal of Information Systems Engineering and Management
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model's learning progress. . The loss array represents the loss values obtained during the training phase, while the val_loss array contains the loss values obtained on a separate validation dataset. The plot helps us visualize the training and validation loss trends over the epochs. The x axis represents the number of epochs, while the y axis represents the corresponding loss values. The blue line corresponds to the training loss, and the orange line represents the validation loss. The plot provides an overview of how the model's performance evolves during the training process. Ideally, we want to see both the training and validation loss decrease over time, indicating that the model is learning and generalizing well. The legend, located on the plot, helps distinguish between the training and validation loss lines. The legend also serves as a reference for understanding which line corresponds to each dataset. Analyzing the plot can help identify potential issues, such as overfitting or underfitting. Overfitting occurs when the model performs well on the training data but poorly on the validation data, resulting in a large gap between the training and validation loss lines. On the other hand, underfitting occurs when

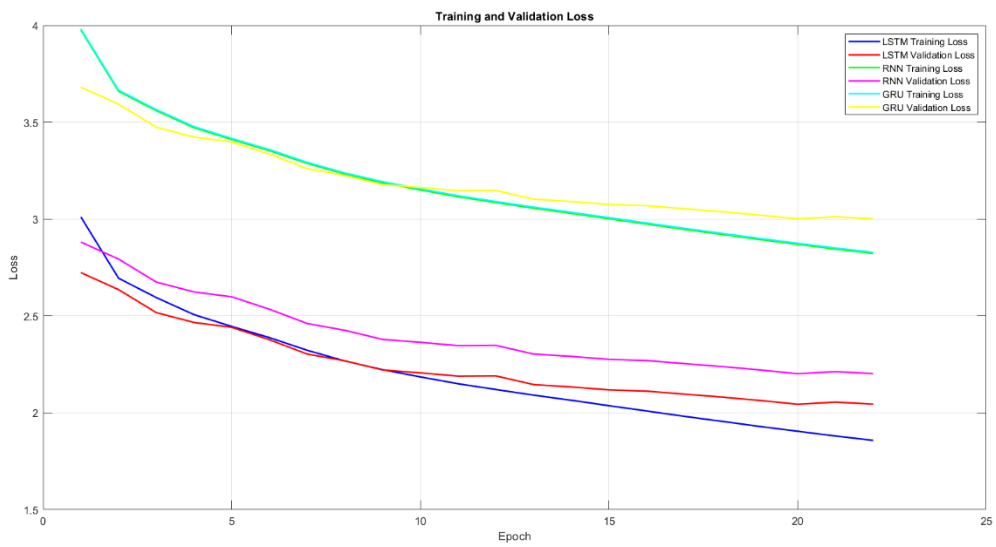

Figure3: training process of Training Loss , Validation Loss of models LSTM, RNN, GRU

The provided figure show the training and validation loss values for three distinct models (LSTM, RNN, and GRU) across 22 epochs. Training Loss and Validation Loss serve as crucial metrics to evaluate the performance of machine learning models during the training process. For instance, in the first epoch, the LSTM model demonstrates the lowest training and validation loss, suggesting its superior performance compared to the RNN and GRU models at that stage in Epoch 1: LSTM: Training Loss = 3.0112, Validation Loss = 2.7238 RNN: Training Loss = 3.97608853, Validation Loss = 2.88141308 GRU: Training Loss = 3.98179278, Validation Loss = 3.68096694. However, it is important to consider the overall trend and examine the complete range of epochs to form a comprehensive assessment. The plot begins at epoch 1 and extends to the maximum epoch value specified in the data. Each epoch is represented on the x axis of the plot. The y axis represents the loss values, which indicate how well the models are performing during training and validation. The lines in the plot are color coded to distinguish between the different models: The training loss values for the LSTM model are plotted as a blue line. The validation loss values for the LSTM model are plotted as a red line. The training loss values for the RNN model are plotted as a green line. The validation loss values for the RNN model are plotted as a magenta line. The training loss values

Journal of Information Systems Engineering and Management
2025, 10(39s)
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https://www.jisem-journal.com/ **Research Article**

for the GRU model are plotted as a cyan line. The validation loss values for the GRU model are plotted as a yellow line.

the table 5 provided displays a collection of reviews, their original summaries, and the predicted summaries generated by a LSTM model. Each row represents a different review and its associated information. The reviews cover a variety of products and experiences, ranging from dog treats to coffee holders, bar drinks, and diabetic friendly drink mixes. The original summaries reflect the essence of each review in a concise manner, capturing aspects such as taste, convenience, quality, and preference. The predicted summaries are generated by a model, likely using natural language processing techniques. The model attempts to summarize the reviews based on their content, providing a condensed version that captures the main sentiment or key features. It is important to note that the accuracy and quality of the predicted summaries depend on the performance and training of the model. Analyzing the table, we can observe that the predicted summaries generally align with the overall sentiment of the original reviews. For example, positive reviews often result in positive predicted summaries, highlighting words such as "great," "delicious," or "yummy." Similarly, when reviewers express their dogs' love for certain products, the predicted summaries reflect that sentiment. Overall, the table represents a comparison between the original and predicted summaries for a range of diverse reviews. It demonstrates the attempt to automate the summarization process using a model, showcasing the model's ability to capture the essence of the reviews, albeit with varying levels of accuracy.

Table5: displays a collection of reviews, their original summaries, and the predicted summaries generated by a LSTM model.

Review	Original Summary	Predicted of RNN,|GRU, LSTM
Review 1	our dogs will do anything for greenie	great for puppies
Review 2	great bar at great price	delicious
Review 3	easy to use coffee holder	great coffee
Review 4	smaller than expected	delicious
Review 5	yummy	great product
Review 6	cheesy	good
Review 7	delicious item	great for the go
Review 8	excellent deal	best dog food
Review 9	my dog loves these	my dog loves these
Review 10	fabulous product	delicious
Review 11	love this	great rice
Review 12	my dogs love them	great product
Review 13	mustard	great product
Review 14	here come	my dogs love it
Review 15	the coffee and the service was great	great coffee
Review 16	very smooth coffee and great liked this	great coffee
Review 17	nice	great product
Review 18	great diabetic friendly drink mix highly recommended	great tea

Overall, it's important to consider the complete testing process and analyze the trends across all epochs to make a comprehensive assessment of the models' performance. the final test and validation loss values for each model. The LSTM model achieved the lowest loss of 2.0448, indicating its superior performance compared to the RNN and GRU models. The RNN model exhibited a loss of 2.20241308. The GRU model had a loss of 3.00196694 among the three models.

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CONCLUSION:

In this study, we presented a comprehensive method for analyzing customer perception of a specific product in Amazon fine food reviews. By applying the TextRank algorithm and implementing LSTM, RNN, and GRU models, we were able to extract important information from the reviews and generate a summary of customer perception. The preprocessing steps, such as data cleaning, language and duplicate value removal, and score distribution analysis, ensured the quality of the dataset. Resampling techniques addressed class imbalance, enhancing the model's performance.The results of the model training process showed a gradual decrease in loss values over the epochs, indicating the learning progress of the models. The validation loss also decreased, suggesting that the selected models were able to generalize well to unseen data. The total training time was approximately 61 minutes, with an average of 167 seconds per epoch. The proposed method achieved promising results in capturing the key aspects of customer perception in Amazon fine food reviews.The value of the results lies in its potential applications in understanding customer sentiment and opinion about specific products. By summarizing and analyzing a large number of reviews, businesses can gain insights into customer preferences, identify areas for improvement, and make data driven decisions. The proposed method offers a systematic approach to extract valuable information from textual data and can be extended to other domains beyond Amazon fine food reviews. Further research can focus on enhancing the models' performance, exploring other algorithms, and incorporating additional features to improve the accuracy and comprehensiveness of the generated summaries. it's important to consider the complete testing process and analyze the trends across all epochs to make a comprehensive assessment of the models' performance. the final test and validation loss values for each model. The LSTM model achieved the lowest loss of 2.0448, indicating its superior performance compared to the RNN and GRU models. The RNN model exhibited a loss of 2.20241308. The GRU model had a loss of 3.00196694 among the three models.

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