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Dynamic Classification of Sentiments from Restaurant Reviews Using Novel Fuzzy-Encoded LSTM

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Abstract - User reviews on social media have sparked a surge in interest in the application of sentiment analysis to provide feedback to the government, public and commercial sectors. Sentiment analysis, spam identification, sarcasm detection and news classification are just few of the uses of text mining. For many firms, classifying reviews based on user feelings is a significant and collaborative effort. In recent years, machine learning models and handcrafted features have been used to study text classification, however they have failed to produce encouraging results for short text categorization. Deep neural network based Long Short-Term Memory (LSTM) and Fuzzy logic model with incremental learning is suggested in this paper. On the basis of F1-score, accuracy, precision and recall, suggested model was tested on a large dataset of hotel reviews. This study is a categorization analysis of hotel review feelings provided by hotel customers. When word embedding is paired with LSTM, findings show that the suggested model outperforms current best-practice methods, with an accuracy 81.04%, precision 77.81%, recall 80.63% and F1-score 75.44%. The efficiency of the proposed model on any sort of review categorization job is demonstrated by these encouraging findings.

Keywords*:* *Sentiment Analysis, Fuzzy, LSTM, Deep Neural Network, Natural Language Processing (NLP), Word Embedding, Text Mining;*

1. INTRODUCTION

Electronic word-of-mouth (eWOM) [1] is defined as "all informal messages addressed towards customers using Internet-based technologies associated to the usage or quality of particular goods and services, or their suppliers." Online reviews are the most popular type of eWOM and they are also the most important. eWOM has a major influence on customer perceptions and purchasing behavior, as well as commercial consequences, in various product categories, such as books. eWOM appears to be especially significant for experience products. Hotels, for example, are examples of goods or services whose quality cannot be easily appraised before to use. Information from other consumers who share their experiences in online reviews is considered as more independent and trustworthy than business information in such circumstances. In the travel industry, roughly two-thirds of US Web users relied on media content for travel information. When it comes to booking travel, more than 74% of people depend on reviews from other consumers.

As a result, internet reviews are a valuable source of information for potential hotel guests, and they influence trust, enjoyment, and willingness to pay. [2]. As a result, hotel performance is influenced by internet reviews. Online reviews have been proven to impact hotel occupancy, RevPar ("revenue per available room") and pricing. The quantity and quality of internet reviews have an impact on consumer behavior. Online comments have been proven to increase awareness, suggesting that ratings, rather than the volume of reviews, have a substantial influence on RevPar. What can hotel marketing managers do to improve hotel performance by increasing the number and quality of online reviews? As part of tactics for digital marketing, customer feedback is continuously watched and analyzed. The model only keeps track of a dynamic set of seen classes, which means that new classes may be added or withdrawn without having to retrain the model.

2. RELATED WORK

Sentiment Analysis (SA) is broadly categorized into three levels: i) document-level, ii) phrase-level and iii) aspect-level [3]. SA at document-level is based on the assumption that the entire text only contains ideas on one topic. In many cases, this is simply illogical. SA at phrase-level, on the other hand, believes that each sentence communicates only one subject. It is common, however, for a single sentence to contain multiple themes (i.e., facets) or opposing viewpoints. The determined sentiment polarity for document- as well as sentence-level SA is based on the complete document / sentence. SA at aspect-level, on the other hand, seeks to ascertain the polarity of stated sentiment for each aspect under consideration. This enables a more in-depth investigation using the review's supplemental data.

As a critical subtask of SA, aspect-level SA has sparked the interest of both industry and academia [4]. In the academic disciplines of semantic Web and computational linguistics, aspect-level SA has recently been a hot topic [5-7]. Aspect-level SA (aspect extraction) is used to locate and infer the expressed sentiment for each of the aspects (also known as aspect-level sentiment classification - ASC). Several researchers have used deep learning to solve the challenge of ASC. This permits us to focus on current discoveries rather than repeating findings that have already been published [3], [8-10]. ASC appears to be doing well in the area of deep learning. The purpose of ASC is to see if user opinions stated in reviews/tweets are positive, negative, or neutral on particular aspects (aspect categories or aspect keywords).

Aspect-based SA [5], [11] is a core task in SA research that is broken down into several subtasks: aspect extraction [12-14], opinion identification [15-16] and ASC [15-19]. Previous research [20-21] attempted to tackle these sub-tasks at the same time, with each sub-task receiving the majority of the research time. This research focuses on deep learning approaches to solving the ASC problem. Unlike document- and sentence-level sentiment categorization, ASC examines both the sentiment and the target information. There will always be a target for an emotion. As previously stated, a target is typically an entity or a trait of an entity. Both entities and aspects are referred to as "aspects." Given a phrase and an aspect, ASC attempts to infer the polarity/orientation of a statement's sentiment toward that aspect. Lexicons and syntactic characteristics-based Machine learning models are used in most traditional ASC techniques [15], [18], and [22]. The labour-intensive hand-crafted feature quality is critical to the models' performance. As a result, current research is focused on creating full deep neural network models from start to end.

RecNN [23] is a neural network that learns how to create structure of a directed acyclic graph. It can be compared to a generalised recurrent neural network (RNN). The sentiment categorization for the specified input sentence is then performed using the representation of a sentence. Dong et al. [25] and Nguyen et al. [26] applied Tree-based RecNN to ASC. RecNN was first used in ASC by Dong et al. [25], who presented an "Adaptable Recursive Neural Network" (AdaRNN). Based on context and grammatical structure, AdaRNN learns to anticipate the emotion polarity of words towards the aspect. To predict emotion polarities distribution, the softmax classifier was used. From sentence dependency tree of specific phrase and target aspect, a binary dependency tree was created. It expressed grammatical links connected to the aspect in a natural way.

The RNN is useful in a number of (linguistic) sequence learning situations. The vast majority of current ASC techniques [27-31] utilise RNN as well. In this area, there are three sub classes of models: RNN, bi-directional RNN (Bi-RNN), and hierarchical RNN (HRNN). A Target-dependent LSTM (TD-LSTM) and a target-connection LSTM (TC-LSTM) is proposed by Tang et al. [28], which used RNN in ASC to capture semantic interactions between the aspect and its context words in a more flexible manner. To replicate phrase syntax and semantics, as well as the interaction between the aspect and its context words, Zhang et al. [27] adopted gated neural network topologies. HRNN was designed in response to Ruder et al. [31] recommendation to use a hierarchical bidirectional LSTM model for ASC that could learn both intra and inter sentence linkages. Incremental learning for SA using LSTM-RNN and hybrid LSTM-SVM are proposed in [24][30].

Successful application of the attention mechanism has been made in a number of natural language processing (NLP) applications [31], including neural machine translation [32-34], question answering [34-35], and machine understanding [36-37]. ASC was recently introduced to a number of AB-RNN models, allowing them to accurately handle the phrase's important sections in connection to the selected aspect. Basic AB-RNN models and interactive AB-RNN models are the two types of AB-RNN models for ASC. Several works have focused on enhancing fundamental attention RNN models [29], [38-40], [42-45]. ASC has also been studied using interactive attention-based models [46–50]. Ma et al. [46], for example, suggested an interactive attention mechanism that learns attentions in real time from a specific aspect and the environment. Previous state-of-the-art techniques, which relied on naive concatenations to imitate word-aspect similarity, were hampered by this.

Natural language processing (NLP) [52] uses convolutional neural networks (CNNs) [51] to recognise local patterns. CNN can distinguish between local and global representations in a text. For ASC, CNN was used in a few experiments [53–56]. To include aspect information into CNN, Huang et al. [50] used parameterized filters and parameterized gates. Proximity technique is used by Li et al. [55] to scale the convolutional layer's input according to the spatial value of the word and aspect. Fan et al. [54] suggested an attention-based convolutional memory network capable of capturing single-word and multi-word phrases in sentences for ASC.

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Using the interaction between the aspect, its left context, and its right context, Zheng et al. [50] presented a “Left-Center-Right separated neural network with Rotatory attention mechanism” (LCR-Rot). A context2target attention system was developed concurrently to focus on the aspect's essential phrases, resulting in a left- and right-aware representation of the aspect. Finally, using the final representation of the sentence, the softmax function was applied to predict sentiment polarity.

Furthermore, He et al. [41] developed a pre-trained and multi-task learning (PRET+MULT) strategy to transfer information from a document-level sentiment classification dataset to ASC using an attentive LSTM model. ASC's performance was improved by using data from document-level sentiment classification databases. “Multi-Granularity Alignment Network” (MGAN) was introduced by Li et al. [60], a new system that simultaneously aligns aspect-granularity and aspect-specific feature representations across domains [1]. S. L. Bangare et al. [61, 62] worked in Image processing, Machine learning, and IoT domain. S. D. Pande et al. implemented the latest variant of CNN termed as capsule network for medicinal leaf classification [63, 64]. P. S. Bangare et al. [65] have proposed object detection work. N. Shelke et al. [66] used LRA-DNN approach. S. Gupta et al. [67] has extracted emotion features. G. Awate et al. [68] applied the CNN work. As indicated by the literature, an algorithm that dynamically classifies the sentiment of a text is plainly needed. The proposed method is designed in such a way that it creates new classes on the fly and begins categorising them without interfering with the categorization of existing classes. The proposed system is designed to address this gap in the literature. The proposed strategy proved successful when tested on the Yelp dataset. The suggested system design is compared against a variety of algorithms in the findings and discussion chapter and the results are published.

DATASETS –

Yelp.com is a popular online directory and review site with a large user base. The data was collected as part of the Yelp Dataset Challenge, which is open to the public and accessible through the Yelp and Kaggle websites. The data for this project came from the Kaggle repository. There are five CSV files in the Yelp dataset: business, users, reviews, check-in and tips. Because restaurants are the most common form of company, this study focuses mostly on this industry. Some of the database's findings are depicted in Figure 1.

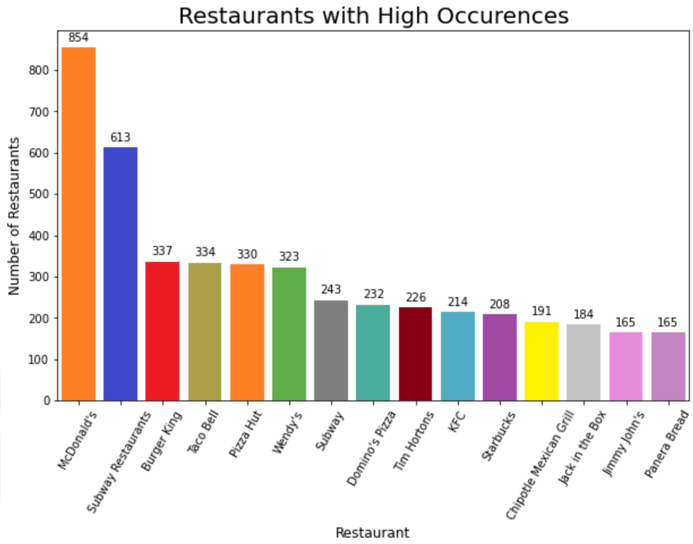

Figure 1 maximum occurrences of the restaurants from yelp dataset

Fast-food restaurants are far more common than other eateries, according to research. Sorting Yelp reviews into categories that are relevant Users of Yelp offer businesses and services ratings and post reviews. Other Yelp users may use these reviews and ratings to assess a business or service and make a decision based on them. Ratings are useful for describing the overall experience, but they do not account for the circumstances that led to the reviewer's experience. Consider the following example from a four-star restaurant's Yelp review:

"They have the best happy hours; the food is good and service is even better. When it is winter, we become regulars". It's tough to guess why the user gave the eatery four stars based just on the rating. However, it is not difficult to discern from the review that it discusses "excellent cuisine," "service," and "deals/discounts" (happy hours).

We were able to identify crucial categories that appear often in the evaluations after a cursory assessment of a few hundred reviews. "Food," "Service," "Ambience," "Deals/Discounts," and "Worthiness" are among the five categories we discovered. The "Food" and "Service" categories are straightforward. The "Ambience" category refers to the decor, as well as the overall appearance and feel of the establishment. The "Deals & Discounts" category corresponds to deals made during happy hours or venue-sponsored promotions. The category "Worthiness" may be stated as "worth for money." Users frequently give their opinion on whether the whole experience was worthwhile. It's vital to notice that the "Worthiness" category is distinct from Yelp's existing "Price" characteristic. The term "price" refers to the cost of the venue, whether it is "cheap," "expensive," or "very expensive." This analysis can assist other customers / users in making a more customised decision, especially if

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they do not have a lot of time to read reviews. Furthermore, this type of classification may be used to rate restaurants based on this analysis. The challenge of categorising a review into appropriate categories became a learning problem. A review, on the other hand, is neither a simple binary classification nor a multi-class classification because it is concerned with multiple categories at once. It's more of a categorization challenge with several labels. Using this categorisation, Yelp may create some fascinating features.

Feature Extraction and Normalization

We discovered two types of features: i) star ratings and (ii) textual features. For star ratings, we created three binary categories that indicate 1-2 stars, 3 stars and 4-5 stars, respectively. Before collecting textual features, we first normalised the review text by turning it to lowercase and removing the special characters. Because the stop words are crucial for understanding user attitudes, they were not eliminated. The cleaned text is next tokenized to collect unigrams and determine their frequency across the corpus. As a result, there are 54,121 different unigrams. This feature collection only considers unigrams with a frequency larger than 300, yielding 375 unigrams. In the same method, we get 208 bigrams and 120 trigrams.

It is not a straightforward binary classification exercise to categorise a review into various categories. Each review can be separated into various categories because a reviewer may cover a variety of topics in his or her assessment. Creating a binary classifier for each category is one of the most popular and possibly simplest techniques to dealing with a large number of categories. As a result, we build five binary classifiers for the categories of cuisine, service, atmosphere, bargains, and merit. To do so, we'll divide the dataset into five separate datasets, each with data of a single category.

Consider a smaller version of our dataset with only four categories to grasp the concept (food, ambience, service and deals). We constructed four distinct datasets from the original dataset, each of which is connected with a specific category, as shown in Figure 2. The derived dataset for the "food" category, for example, will only have one label. All datapoints in the original dataset with a "1" for "food" will get a label of "1." Similarly, all datapoints in the original dataset with a service of '1' will have a label of '1' in the dataset created for "service." This is done for each and every one of the dataset's categories. For each category, a binary classifier predicts whether a new review belongs to that category given a new review. The sum of all binary predictors generates the final prediction.

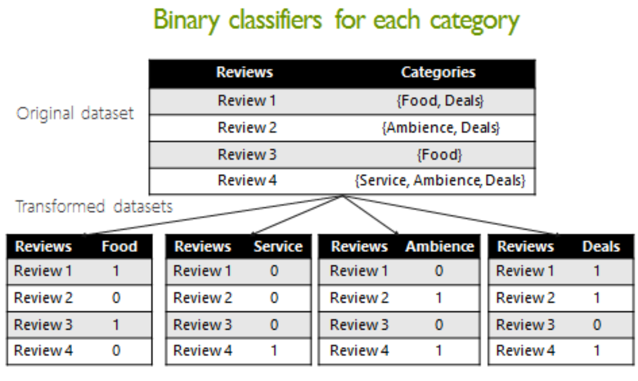

Figure 2 binary classifier of each category

Any binary classifier, such as closest neighbour, LSTM, decision trees and so on, may be utilised with this technique after the dataset has been converted into four separate datasets. Although this method is straightforward and examines each group separately. As a result, the link between categories is overlooked. This assumption could be incorrect, especially if the groups share certain characteristics. For example, in our scenario, most individuals believe that if they obtain a good bargain, the restaurant is worth visiting. This suggests that the categories of "deals" and "worthiness" are linked. We also noticed a link between the "service" and "ambience" categories. It's possible that the connection is great at times and low at others. However, we felt it was important to account for in our circumstance.

We interpreted each subset of L as a separate category to allow for cross-category correlation. The letter L denotes the collection of all categories, which is also known as targets. L stands for "Food, Service, Ambience, and Deals." Figure 2 depicts how Review-1, "Food, Deals" target is reduced to a single target with the value "1001." As with Review 2, "Ambience, Deals" is renamed "0011." Then we learn : $X \rightarrow P(L)$, a multi-class classifier in where X is the review and $P(L)$ is the powerset of L, which includes all possible category subsets. This method takes cross-category correlations into account, but it has issues with the large number of category subsets. This method will produce 25 different forecasting objectives if we have five categories, for example, the majority of which will only require a few datapoints to learn. If there is a large training dataset that includes all (or at least the majority) of the accessible targets to forecast, this strategy may function well.

By looking at category correlation and ignoring the large number of subgroups formed by the prior method, we intended to achieve the best of both worlds. As a result, we implement a ensemble of classifiers, each of which is trained individually on a tiny subset (k) of categories. Assume there are four categories: food, service, atmosphere and bargains. The subset's size is set to two. As a result, we create a total of

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6 classifiers for the further categories: {"Food, Ambience", "Food, Service", "Service, Ambience", "Food, Deals", "Ambience, Deals", (Service, Deals). This technique takes into account category correlations while also creating a minimal number of targets by examining only a small sample of categories for each classifier.

INCREMENTAL LEARNING with Fuzzy encoded LSTM:

Incremental learning is a machine learning paradigm in which the learning process occurs whenever new instances are presented, and it updates what has been learnt in response to the new example(s). The most notable distinction between incremental learning and classical machine learning is that it does not presume the existence of a sufficient training set prior to beginning the learning process; instead, training instances arise over time.

In classical supervised learning, the closed-world assumption is that the classes shown in testing must have emerged during training. However, in real-world applications, this assumption is frequently broken. For example, on a social networking site, new themes surface on a regular basis and in e-commerce, new product categories develop on a daily basis. It's difficult for a model to perform properly in such open contexts if it can't recognise new/unknown subjects or items. In such circumstances, a good model must be able to (1) reject instances from unknown classes (not encountered in training) and (2) learn new/unknown classes progressively to extend the existing model. This is referred to as open-world learning (OWL). The essential innovation is that the model simply keeps track of a dynamic set of viewed classes, allowing new classes to be added or removed without having to retrain the model.

There is already a large quantity of unstructured data available and the number is growing all the time. Twitter, support forums, blogs, news, ecommerce - product reviews, consumer comments and so on are just a few examples. As the time frame slides/advances, the contexts of these sources slowly update as well. As a result, existing models that were trained on existing data must be updated. When new data becomes available after a given period of time, the existing model should be updated rather than retrained.

Almost all machine learning and deep learning algorithms use in-memory analytics, which means they require training data to be stored in memory. There is a limit to how much data can be used to train ML / DL models. As a result, models should be updated in batches or on a part-by-part basis.

New data will be accessible in the future with somewhat different context, such as new food items, new service techniques in restaurants and new functions in electronics gadgets. As a result, these characteristics should be thoroughly examined without retraining the existing model. Only new data and prior model parameters should be used to UPDATED / INCREMENTALLY LEARN the model.

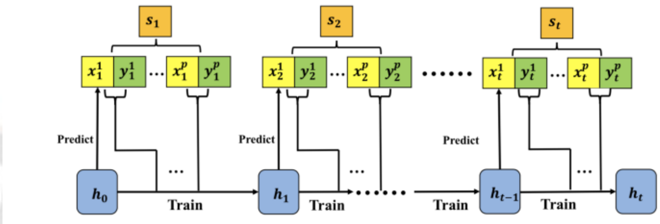

Figure 3. Incremental learning framework

Model $h_1, h_2, \ldots, h_t$ are generated for each block of new data with block size p, where (x_t^i, y_t^i) signifies the i-th new data for the t-th block. Depends exclusively on the model h_{t-1} and the most recent block of new data s_t, which consists of p samples with p strictly limited; for example, if $p = 16$, then will forecast for each new data and update the model with a block of 16 new data. The problem of catastrophic forgetting affects all incremental learning techniques. Let's imagine we start with a model h_{base} that was trained on n classes and then add m new classes to make the model h_{new}. In an ideal world, we'd like h_{new} to be able to reliably forecast all $n + m$ classes. In this research, we provide a modified cross-distillation loss and a two-step learning technique to handle this problem in an online environment.

Figure 4 represents the Fuzzy encoded LSTM which take input in the form of sequential data and output of it is in the form of reconstructed results.

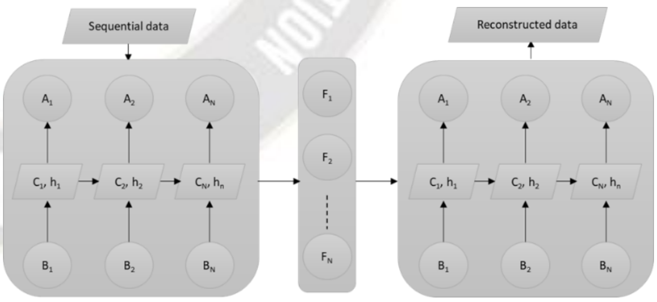

Figure 4. Fuzzy encoded LSTM

Proposed Fuzzy encoded LSTM index FL_k^*, which is also the triangular membership function, is illustrated in following equation,

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$$FL_k^* = (FL_k^L, FL_k^M, FL_k^U) = \big(\mathrm{m}\ \ (FL_{k+(T-W+1)\times m}, FL_{k+(T-W+2)\times m}, \dots, FL_{k+T\times m}), \\ FL_k, \mathrm{m}\ \ (FL_{k+(T-W+1)\times m}, FL_{k+(T-W+2)\times m}, \dots, FL_{k+T\times m})\big), k = 1, \dots, m \quad (1)$$

where FL_k^L is $W-$ period lower bound, FL_k^M is W–period smoothing-operators $(1 \le W \le T)$ and FL_k^U is W–period upper bound, respectively.

For the classification of the reviews from the text first it is important to find out similarities as well as dissimilarities within the cluster. For doing so the fuzzy encoded LSTM is used in recursive mode to get the maximum accurate results. Therefore, the triangular fuzzy function is used to do so.

$$\widetilde{FLSI_{k+(T+v)}^{I}} = \left(flsi_{k+(T+v)}^{LTr} \times FL_k^L \times \varepsilon, flsi_{k+(T+v)}^{MTr} \times FL_k^M \times \varepsilon, flsi_{k+(T+v)}^{UTr} \times FL_k^U \times \varepsilon\right) \quad (2)$$

Where $\widetilde{FLSI_{k+(T+v)}^{I}}$ gives the fuzzy similarity index value, $flsi_{k+(T+v)}^{LTr}$ represents the minimum allowable similarity index, $flsi_{k+(T+v)}^{MTr}$ mean value of similarity index and $flsi_{k+(T+v)}^{UTr}$ maximum allowable similarity index.

Therefore, the mathematical model of the fuzzy encoded LSTM is with minimum, mean and maximum value is represented as,

$$\begin{aligned} flf_{LTr}(x_i) &= o_{Li} \otimes \tan\ h(c_{Li}) \\ flf_{MTr}(x_i) &= o_{Mi} \otimes \tan\ h(c_{Mi}) \quad (3) \\ flf_{UTr}(x_i) &= o_{Ui} \otimes \tan\ h(c_{Ui}) \end{aligned}$$

Equation 3 clearly indicates that the flf_{LTr}, flf_{MTr} and flf_{UTr} is of the tan hyperbolic in nature. The fuzzy rules selected for encoding are tan hyperbolic in nature.

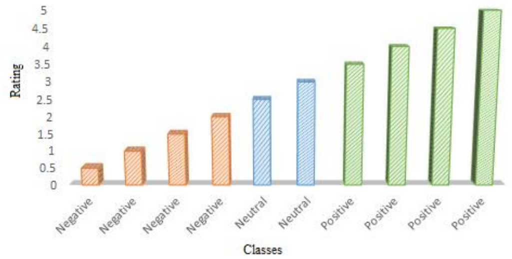

Figure . classes of classification along with rating

Here in the research work the three classes has been addressed. The three classes are positive, negative and neutral. The consideration of these classes along with rating is presented in figure 5 in diagrammatical format.

Figure 5 shows the consideration of rating from 0.5 to 5. Rating from 0.5 to 2 is considered as negative. Rating of 2.5 and 3 is consider as neutral. And rating from 3 to 5 is consider as positive.

Result and Discussion

The proposed approach is tested on the Yelp restaurant review dataset. The performance parameters of the proposed fuzzy LSTM are tabulated in table 1.

Evaluation Criteria		Value (%)
Accuracy	Negative	81.49
	Neutral	79.23
	Positive	81.04
Precision	Negative	73.76
	Neutral	71.75
	Positive	87.92
Recall	Negative	74.76
	Neutral	68.45
	Positive	98.67
F1 score	Negative	72.96
	Neutral	61.48
	Positive	91.89

Table 1 Performance parameters of the proposed fuzzy LSTM

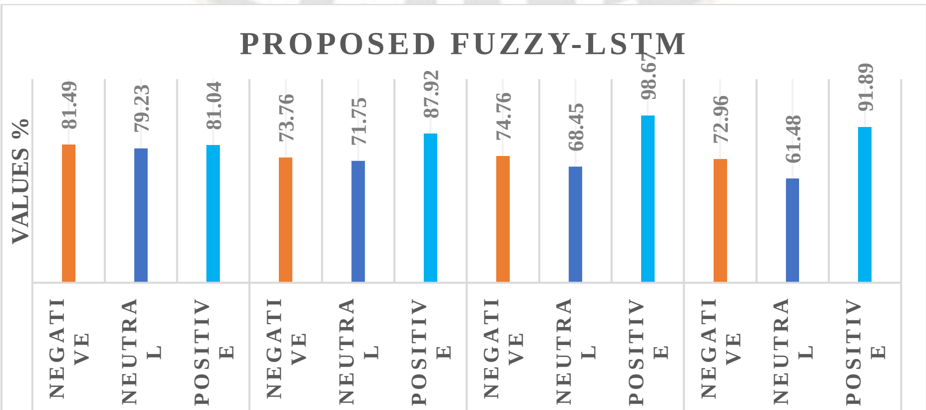

Figure 6 Performance parameters of the proposed fuzzy LSTM

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Figure 6 show the performance results of the fuzzy LSTM. It gives overall accuracy of the classification. It also displays precision, recall, and F1 score diagrammatically for positive, neutral, and negative classes.

The performance parameters tabulated in table 1 are of the three classes. By using incremental learning, the automatic classes have been generated. The performance parameters for the incrementing automated classes have been tested and tabulated in table 2. By adjusting the iterations firstly only three aspects Ambiance, food and service have been considered.

Then the extra class (aspect) called price is automatically get generated. After that after every particular iteration another 3 aspects have been added by the Proposed System Architecture (PSA). The added aspects are nature, quality and accessibility. After adding every aspect (class) the performance parameters are tabulated in table 2 and it is illustrated diagrammatically figure 7.

	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
3 classes	81.04	77.81	80.63	75.44
4 classes	80.31	76.23	79.23	74.23
5 classes	84.23	79.98	82.71	79.23
6 classes	81.23	81.32	79.02	74.8
7 classes	79.42	80.25	78.98	72.35

Table 2. The performance parameters of the proposed fuzzy LSTM with incremental learning

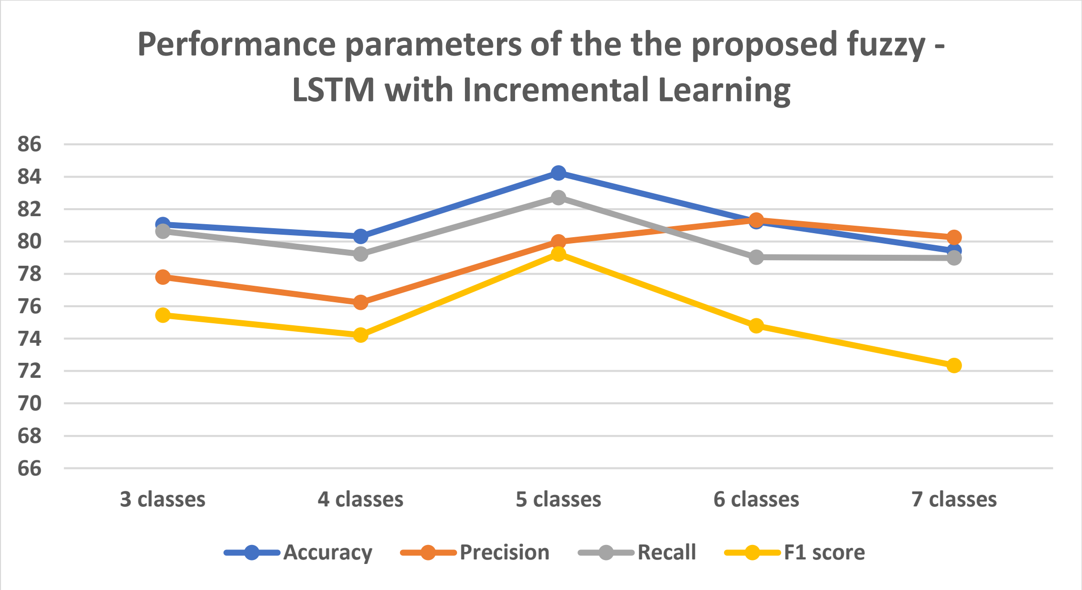

Figure 7. Performance parameters of the proposed fuzzy LSTM with incremental learning

Results of the PSA is compared with the existing systems on the basis of performance parameters. The performance parameters of the PSA along with existing algorithms is tabulated below.

Table 3. Comparison of performance parameters of the proposed system with existing algorithms

	Accuracy			Precision			Recall			F1 Score		
	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral	Positive
Proposed Fuzzy-LSTM	81.49	79.23	81.04	73.76	71.75	87.92	74.76	68.45	98.67	72.96	61.48	91.89
ContextAvg	74.92	72.31	73.48	56.48	51.79	80.49	55.61	29.59	90.11	56.04	37.66	85.03
AEContextAvg	74.49	76.23	75.27	62.09	55.47	81.36	57.65	36.22	90.52	59.79	43.83	85.7
LSTM	75.32	76.7	77.23	63.35	54.55	84.73	61.73	39.8	91.48	62.53	46.02	87.98

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GRU	79.22	76.25	78.75	67.36	59.84	84.35	66.33	37.24	93.27	66.84	45.91	88.58
BiGRU	78.42	75.18	77.14	64.94	53.69	84.19	57.65	40.82	92.17	61.08	46.38	88
BiLSTM	78.52	78.75	78.3	65.13	56.64	85.55	64.8	41.33	91.9	64.96	47.79	88.61
TD-LSTM	81.23	77.14	78.66	72.88	54.55	85.09	65.82	45.92	90.93	69.17	49.86	87.92
TC-LSTM	76.32	77.23	77.41	67.78	55.7	83.69	62.24	42.35	90.93	64.89	48.12	87.16
AT-LSTM	77.48	78.75	78.04	70.06	61.25	81.23	67.27	25	96.29	66.49	35.51	88.12
AT-GRU	79.41	77.14	78.3	67.91	61.21	83.11	64.8	36.22	93.27	66.32	45.51	87.9
AT-BiGRU	77.83	78.66	77.77	65.13	59.84	83.56	64.8	37.24	92.17	64.96	45.91	87.66
AT-BiLSTM	76.79	77.41	78.84	68.45	67.82	82.27	65.31	30.1	95.6	66.84	41.7	88.44
ATAE-GRU	76.34	79.22	76.79	69.49	54.62	81.92	62.76	36.22	91.48	65.95	43.56	86.44
ATAE-LSTM	75.98	78.42	76.79	64.53	57	82.25	66.84	29.08	92.31	65.66	38.51	86.99
ATAE-BiGRU	76.7	78.52	76.34	63.77	50.41	83.67	67.35	31.63	90.8	65.51	38.87	87.09
ATAE-BiLSTM	76.25	78.84	75.98	66.29	53.28	81.46	60.2	33.16	91.76	63.1	40.88	86.3
IAN	75.18	76.79	76.7	64.25	58.06	82.57	63.27	36.73	91.07	63.75	45	86.61
LCRS	78.75	74.49	76.25	69.82	56.44	79.88	60.2	29.08	93.27	64.66	38.38	86.06
CNN	77.14	75.32	75.18	60.44	65.79	79.12	56.12	25.51	93.68	58.2	36.76	85.79
GCAE	78.3	79.22	77.41	64.86	57.43	83.44	73.47	29.59	91.35	68.9	39.06	87.21
MemNet	78.66	74.13	73.39	52.56	52.38	83.29	62.76	33.67	86.95	57.21	40.99	85.08
RAM	75.32	76.49	77.41	67.2	53.25	84.29	64.8	41.84	90.38	65.97	46.86	87.44
CABASC	72.8	81.37	77.68	65.59	55.68	85.75	62.24	50	89.29	63.87	52.69	87.48

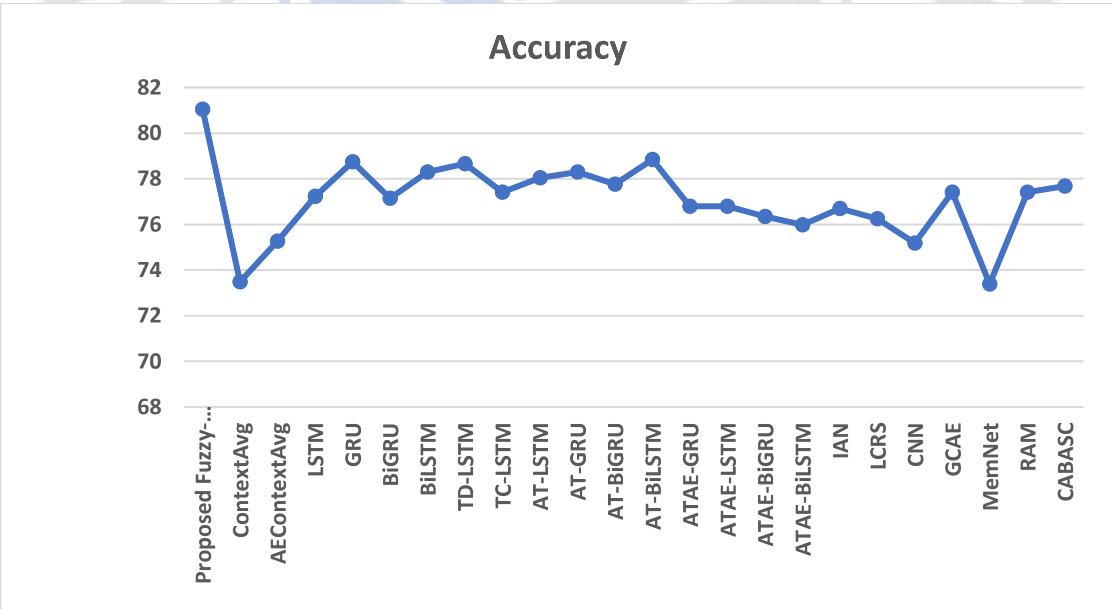

Figure 8. Graphical representation of the accuracy of the PSA along with existing systems

Figure 8 gives accuracy vs classifier graph. The suggested system design has a higher accuracy than any current algorithm. The suggested fuzzy LSTM has an accuracy of 81.04 %. The AT-BiLSTM had the previous maximum accuracy of 78.84 %.

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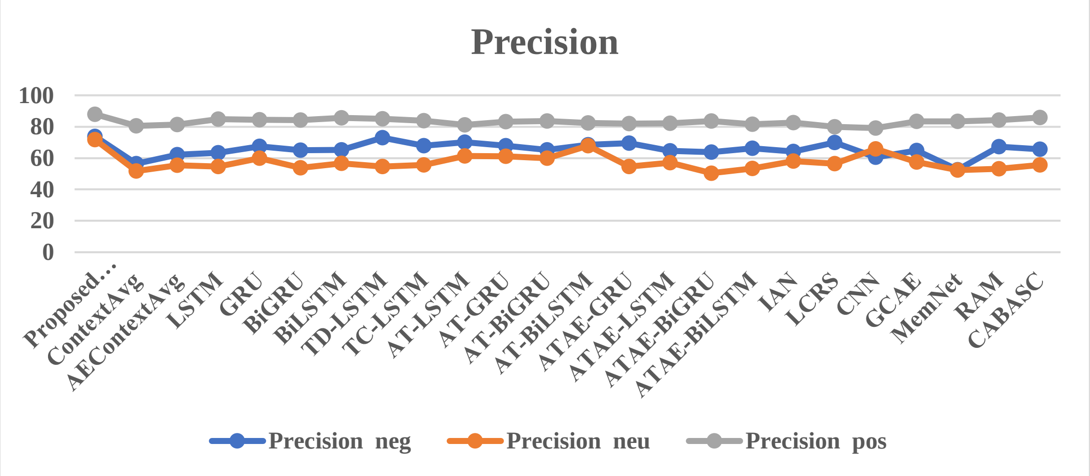

Figure 9. Graphical representation of the precision of the PSA along with existing systems for classification of negative, neutral and positive review

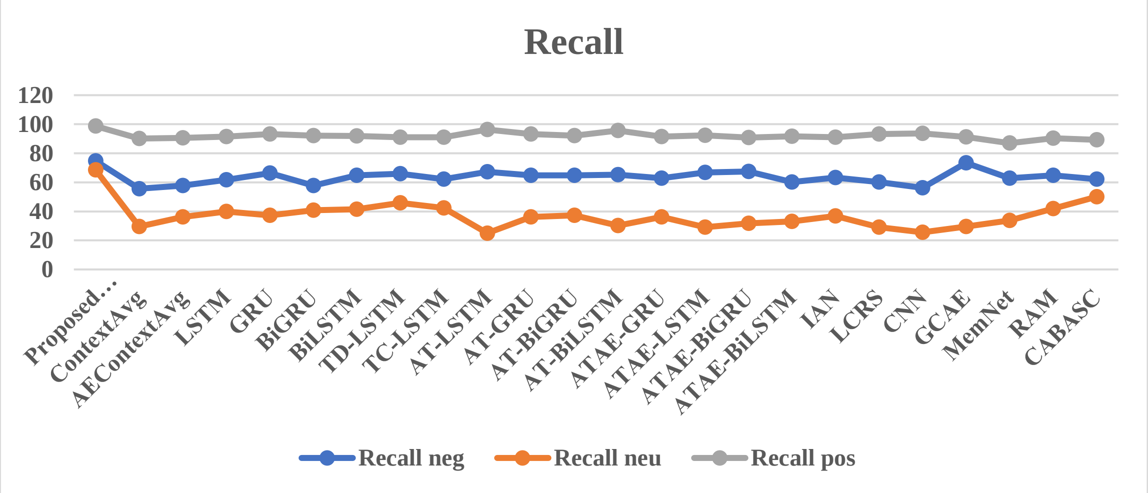

Figure 10. Graphical representation of the Recall value of the PSA along with existing systems for classification of negative, neutral and positive review

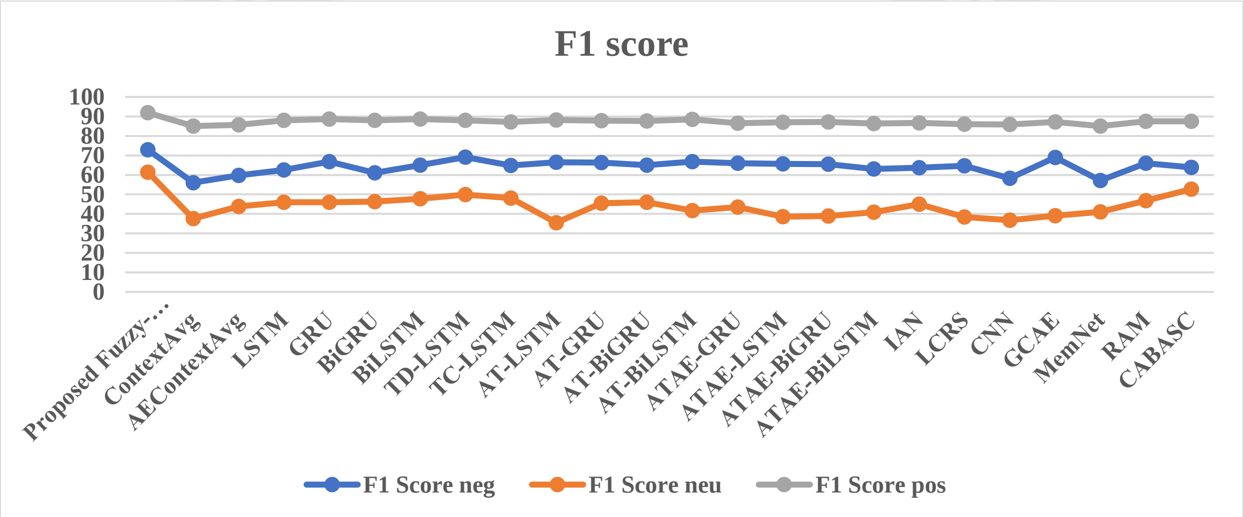

Figure 11. Graphical representation of the F1 score value of the PSA along with existing systems for classification of negative, neutral and positive review

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Figures 9, 10 and 11 indicate that the proposed system's precision, recall, and f1 score are much greater than any existing technique.

CONCLUSION

This suggested deep neural network approach automatically extracts characteristics that are important in the target's final forecast. The fuzzy encoder, LSTM sequence modelling and word embedding assist the model train successfully. In terms of accuracy, precision, recall and f1-score, it gives improved results. In order to automatically expand the number of classes, incremental learning is essential. The suggested fuzzy LSTM has an accuracy of 81.04%, which is significantly higher than the previously evaluated systems. As the number of classes grows, the total classification accuracy remains within acceptable limits. For the five classes, we find a maximum accuracy of 84.23%. The fuzzy LSTM suggested is compared to the other 23 methods. The suggested fuzzy LSTM outperforms the other 23 algorithms on all performance measures.

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