Journal of Theoretical and Applied Information Technology
31st August 2025. Vol.103. No.16

ISSN: **1992-8645** www.jatit.org E-ISSN: **1817-3195**

ANALYSIS OF E-COMMERCE PRODUCT REVIEW FOR TRUST ASSESSMENT USING ENSEMBLED DEEP LEARNING MODEL

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ABSTRACT

In the realm of e-commerce, online reviews plays a vital role in influencing consumer decisions.. Especially there is huge demand in computing the trust of the online reviews to prevent the consumer from misguiding and major impacts of the products of the similar businesses. However many researcher has initiated their trust assessment approaches in online product review using machine learning and deep learning based Artificial intelligence architecture. Despite of several benefits, those approaches faces major challenges in terms of the processing the linguistic features and semantic features. In this paper, a new ensemble deep learning model with sentiment analysis has been designed to evaluate trust in product reviews from the Flipkart platform on providing consumer with reliable deeper insights of the product quality and user experiences. Initially preprocessing of the dataset is carried out to obtain reliable word vector from product reviews containing text data through stop word removal , special character removal , stemming and tokenization processes. Next, N-gram model is used to extract the contextual and behaviour features through linguistic and semantic approaches on token of the word vector. Obtained contextual feature and behaviour word vector is encoded using transformer model. Encoded Word vector is projected to BERT analysis for sentiment extraction. Encoded word vector with sentiment is projected to ensemble deep learning models termed as EDL-RNN+CNN+BIGRU. It composed of Recurrent Neural Networks (RNN), Improved Pooling based Convolutional Neural Networks (IPCNN) and Bidirectional Gated Recurrent Units (BiGRU) model. Finally the complementary strengths of each model is leveraged as it is more robust and effective in capturing the nuanced features of online reviews for sentiment analysis compared to using any single architecture alone. Weighted averaging is a common approach employed to ensemble learning to interface the predictions of individual architectures while assigning different weights to each model's prediction based on its performance on computing the trust on the processing sentiment incorporated encoded feature vector in the layer of the model. Experimental and performance analysis of the proposed ensemble model is carried out using Flipkart dataset which is extracted using the online platform such as kaggle. Performance analysis of the model using cross fold validation of test data is performed to compute the accuracy and effectiveness of the model . On evaluation, model produces 94.2% of accuracy, 94% of precision and 93% of recall which found to be outperforming on comparing it against state of art approaches.

Keywords:*Ensemble Deep learning, RNN, CNN and BGRU.*

1. INTRODUCTION

The proliferation of user-generated content across online social network platforms such as Flipkart, Amazon, and Trip Advisor has significantly transformed the dynamics of consumer opinion sharing[1] on their experience to the product and transactions. Particular surge in user-generated content has granted individuals with unprecedented power to express their opinions, experiences, and sentiments regarding a wide range of services, products, events, and more. Platforms like Flipkart serve as real-time hubs where users can share their thoughts, reactions, and reviews in concise and immediate formats [2]. Amazon, on the other hand, has established itself as a leading e-commerce platform where customers can not only purchase products but also provide detailed feedback and reviews based on their experiences. Similarly, Trip Advisor has emerged as a prominent platform for travelers to share their opinions and recommendations about hotels, restaurants, and tourist attractions [3].

According to the data from Federal Trade Communication(FTC) in united states, it is found that many businesses engages in the deceptive practices including posting fake reviews to the products of their competitor to deceive customer and increase their online sales . To address those challenges, many researcher has been performed to identify and mitigate those circumstances using artificial intelligence approaches. However those model fails to incorporate the semantics and sentiments analysis to analyze the user behaviour. Thus it becomes important to explore solutions to predict the creditability or trust among the online product review posted.

In particular, approaches for sentiment analysis are primarily based on machine learning (ML) techniques and deep learning (DL) techniques with preprocessing and feature extraction approaches. ML algorithms such as Support Vector Machines(SVM)[3], Naive Bayes[4], Decision Trees[5] have been largely employed for sentiment analysis [4]. These approaches typically involves model training to a labeled data consisting of text samples and its sentiment labels (e.g., positive, negative, neutral). On training process, the model determines patterns and features in the text samples that are indicative of multiple sentiments.

Feature extraction methods play a crucial role in sentiment analysis by transforming text data into a structure on which ML algorithms can interpret and process those data effectively. These methods incorporates approaches such as bag-of-words, N-grams, Word embeddings such as Word2Vec, GloVe, and more advanced approaches such as attention mechanisms to prioritize input text during analysis [6].Furthermore, domain-specific sentiment analysis may incorporate additional features or knowledge sources relevant to the particular domain being analyzed. For example, in analyzing social media sentiment, features such as user profiles, timestamps, and social network structures may be considered alongside textual features [7].

Overall, the combination of ML algorithms, and feature extraction methods has led to significant advancements in sentiment analysis on product review analysis applications [8]. In this work, it continues to refine and improve these Deep learning approaches[9] to obtain accurate and nuanced sentiment analysis results. Objective of the work is to model a ensemble model[10] composed of deep learning model to identify the complex features for sentiment analysis and trust assessment [11]. Proposed model should be capable in providing the contextual and behaviour features on incorporation of Bidirectional Encoder Representation Transformer(BERT)[12] and N-Gram Model[13]. Further contribution of the work is as follows

- The work employs various pre-processing techniques tailored specifically for handling textual data from online reviews.
- The work proposes enhanced bigram models that go beyond traditional approaches. These models incorporate semantically similar words to those in n-grams, thereby improving the classification of reviews. This approach accounts for the variability in language usage among reviewers while expressing sentiments.
- The work introduces a novel method that integrates the NBR measure[14] with an ensemble DL model. This ensemble model combines different neural network architectures, including RNN, IPCNN, and BiGRU. The ensemble model, named EDL-RNN+IPCNN+BIGRU, leverages the strengths of each architecture to enhance sentiment analysis performance.

Remaining section of this articles were organized as follows, section 2 provides review of literatures offering comprehensive understanding of the research conducted using machine learning , feature extraction and deep learning architectures. Section 3 provides the design of the proposed ensemble deep learning model termed as EDL-RNN+IPCNN+BIGRU is composed of Recurrent Neural Networks (RNN), Improved Pooling based Convolutional Neural Networks (IPCNN) and Bidirectional Gated Recurrent Units (BiGRU) model. Section 4 mentions the experimental analysis of the proposed ensemble architecture using flipkart dataset extracted online platform and performance analysis of the model is carried out using confusion matrix to metric such as accuracy, precision and recall against state of art approaches. Finally, section 5 concludes the article with major findings with future suggestions.

2. RELATED WORK

In this section, familiar product review and user classification architectures using feature

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

extraction approaches, machine learning architectures and deep learning architectures with sentiment analysis were carried out using various dataset is as follows

He et al.[15] presented a Support Vector Machine based machine learning model with dictionary approach to extract sentiment features from the user review datasets. In this literature, Linear discriminant model is employed to extract the sentiment topics to the review contents as it contains the words with unequal sentiments. Further dictionary model compute the sentiment information on word through incorporation of weighting method with semantic similarity calculations. Extracted sentiment features is projected to SVM classifier to predict the sentiment polarities to the user reviews. Finally evaluation of the model performance proves that it performs better in identifying the sentiment of user accurately on more comprehensive understanding of sentiment features in reviews. Major challenges of the approach is computational complexity. .

Yang et al.[16] presented a hybrid model composed of Lexicon based convolutional Neural Network with Attention-based Bidirectional Gated Recurrent Unit (BiGRU). In this literature, sentiment lexicon is used to enhance the performance of the sentiment feature extraction. Extracted sentiment feature is employed to convolutional Neural Network and Bidirectional Gated Recurrent Unit (BiGRU) on extracting the contextual features to sentiment. Further attention mechanism to weight the contextual features with weight. Finally contextual feature and sentiment feature is classified with increased classification accuracy. Major challenges of the approach is computational complexity during employing hybrid technique.

Hu et al.[18] presented a CISER model which is composed of candidate feature extraction, reviewer credibility analysis, user interest mining, candidate feature sentiment assignment, and recommendation modules to enhance the performance of the recommendation system. In this literature, sentiment analysis has been incorporated to processing the data as feature extraction process to identify the credibility and interest. The credibility assessment of reviewers helps to the mine the user interests. Sentiment analysis of candidate features with credibility-weighted sentiment scoring methods provides personalized recommendations based on user preferences. Model provides the accurate recommendations and it faces challenges on basis of computational complexity.

Rasappan et al. [19] presented Long Short-Term Memory model incorporated Golden Jackal Optimization for Sentiment Analysis (SA) of product reviews. The methodology involves Non linear feature extraction method and sentiment inclined deep learning model for sentiment classification. in this literature, Feature were extracted and selected using Log-term Frequency-based Modified Inverse Class Frequency (LF-MICF) and Improved Grey Wolf Optimizer (IGWO). Finalized sentiment feature is projected to the recurrent neural network with LSTM model to sentiment classification of the review into into negative, positive, or neutral sentiment classes. Model provides the better classification accuracy and it faces challenges on basis of computational complexity

Punetha&Jain[20] presented a game theory based mathematical framework for sentiment classification on processing product review. In this literature, sentiwordnet lexicon model is used to derive the sentiment content review with sentiment score. Further Bayesian Game Model is used to classify the sentiment contents with score is classified as positive or negative. Model provides the better classification accuracy for NLP task with high stability and it faces challenges on basis of computational complexity

Anbumani, &Selvaraj[21] presented a for Convolutional Neural Networks (CNNs) with new activation function for model as sigTan-Beta Activation Function to obtain better sentiment classification results. In this literature, model uses the Word2Vec to preprocessed review content to obtain feature vector. Feature vector is computed using word distances and similarity estimation to group the word vector. Obtained Word vector is projected Convolutional Neural Networks (CNNs) with new activation function for model as sigTan-Beta Activation Function for sentiment classification which dynamically adjusted sentiment feature weights to enhance accuracy. Model provides the better classification accuracy for NLP task with high stability and it faces challenges on basis of computational complexity

Sasikala& Mary[22] presented a Improved Adaptive Neuro-Fuzzy Inference System (IANFIS) for prediction of sentiment in the online reviews. In this literature, Contents-based features, Grades-based feature and Collaborations-based

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

features are obtained using feature extraction techniques. Extracted feature is projected to IANFIS applied weighting factors towards classification of the reviews with sentiments as negative, positive, or neutral. Model provides the better classification accuracy for NLP task with high stability and it faces challenges on basis of computational complexity

Zhang et al., [23] presented a Apriori algorithm with intuitionistic fuzzy TODIM method for sentiment analysis. In this literature, lexicon based approaches is used to extract the contextual features. Extracted Contextual feature is employed to intuitionistic fuzzy TODIM method to extract the sentiment and sentiment orientation to the features. Finally apriori algorithm is employed for sentiment classification. Model provides the better classification accuracy for NLP task with high stability and it faces challenges on basis of computational complexity.

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Jardim& Mora [24] presented a text mining approach to enhance recommendation of tourism services and products. In this literature, clustering algorithm is incorporated to preprocessed use and product information. Their method utilizes customer digital footprints like posts and reviews to gather preferences of user to the products. Further sentiment analysis is incorporated to the clustering approach to group similar content efficiently. Model exhibits high accuracy in user segmentation and sentiment analysis, with support for decision-making. However, challenges may arise in interpreting nuanced language expressions in the across diverse cultural contexts.

3. Proposed Method

In this section, design of the current deep learning architecture entitled is ensemble model which is composed of the Recurrent Neural Networks (RNN),Improved Pooling based Convolutional Neural Networks (IPCNN) and Bidirectional Gated Recurrent Units (BiGRU) is abbreviated as EDL-RNN+CNN+BIGRU has been presented with processing steps. Figure 1 represents the architecture of the present deep learning model towards trust assessment of the online product reviews.

3.1. Data Preprocessing

In this process, data collected through the online platforms are preprocessed among the multiple processes termed as stop words removal and special character removal, stemming or lemmatization and tokenization.

3.1.1. Stop Word Removal

It is to remove the meaningless words from the product reviews of user as it is represented as common words in the natural language. Those words in form of noun ,pronouns articles, preposition and conjunctions were removed as considering it as top words. Hence stop word removal process removes the meaningless words which resides in the review sentences abundantly. Eliminating those common words does not produce any negative consequence to the Prediction task of the deep learning model alternatively it reduces the size of the dataset and model training time.

3.1.2. Special Character Removal

Special character like punctuation, mathematics symbols, accents and paragraph marks has to be removed. Those characters leads to noise and inconsistent results while post processing the text context in the matrix form.

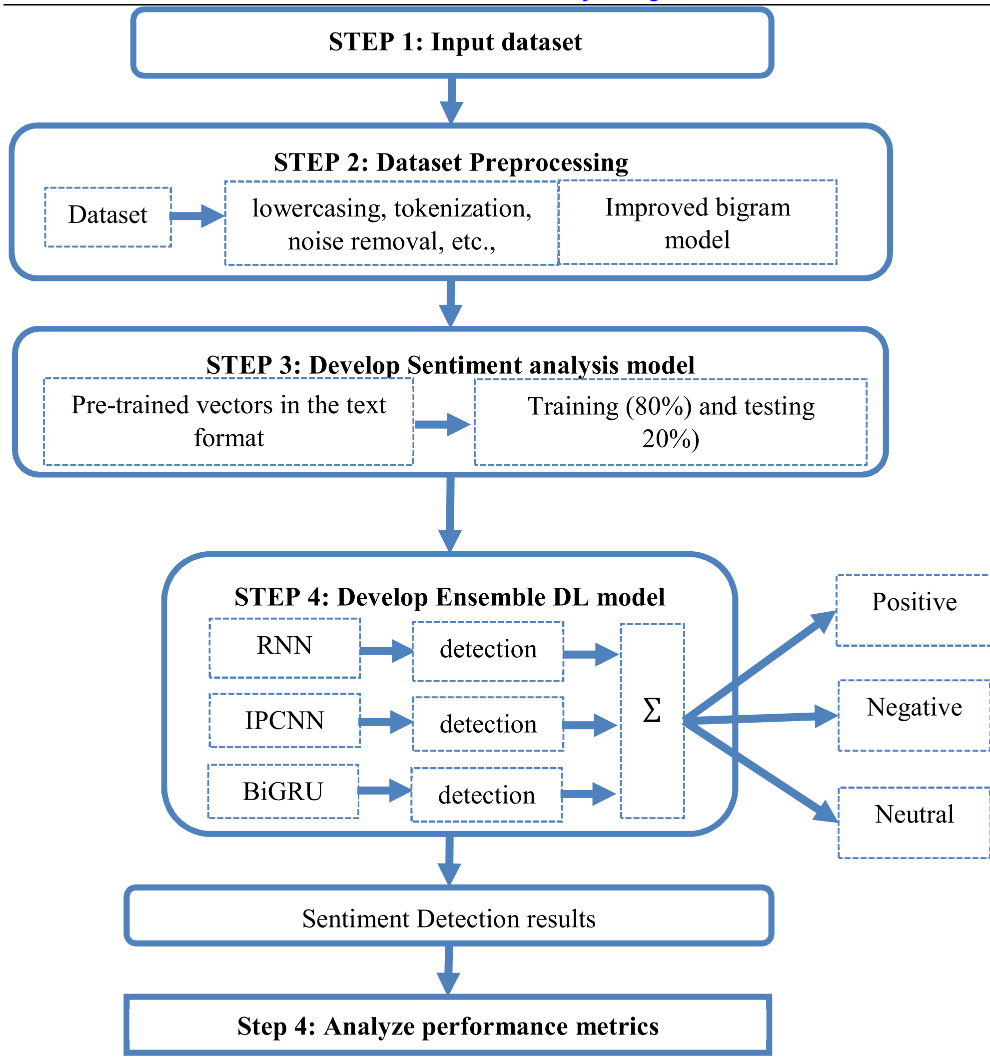

Figure 1: Architecture of the present deep learning model for trust assessment of the online product reviews

3.1.3. Stemming process

It is the another familiar process of reducing the word from its base word which is fastened as suffixes and prefixes or to in the roots of words is considered as lemmas. In other words, it is represented as word normalization technique which eliminate the lemmas. Stemming method is considered as vital process as it produces the outcomes with token representing reduced characters.

3.1.4. Tokenization Process – word-based tokenization

It is to process which splits review sentence into separate meaningful tokens. Token can be effortlessly compiled by the deep learning models and its functions. Token can be characters, words and sub words. In this work, word based tokenization[17] is a represented as splitting process of the sentences eliminates only emojis, whitespaces, delimiters from the sentence from further processing as it is considered as meaningless in sentiment analysis.

3.1.5. Weighting scheme- TF-IDF

Token contains more information for contextual learning instead it is required to extract the best words or token. Term Frequency Inverse Document Frequency(TF_IDF) is employed to obtain significance of the word to the particular review. It is considered as exploratory data analysis to analyze the data distribution of the review. Term Frequency(TF) is to compute no of occurrence of the words in the product review collection. Inverse Document Frequency(IDF) is to compute the rarity of the word in the product review collection. Computation of the TF-IDF computation is represented in the equation 1 is as follows

$$Tf_{u,wi} = \frac{TF'}{\sum_{wi \in W}(TF')} \text{....Eq.1}$$

Where TF' is the TF value of w_i in review r.

W is the set of keywords

3.2. N-gram model - Feature Extraction

N-gram model is to gather patterns and relationship among the sequence of the words(token). Further it captures the contextual information and semantics within the sequence of the words and its semantically similar words from preprocessed reviews word collection is to predict the probability of the specified tokens with type of sentiment on contextual relationship. Gathered words is processed in matrix. Matrix computation of the words (tokens) of the review produces following prediction

3.2.1. Positive Prediction

Probability of the positive prediction on the set of the token on the reviews is identified on basis of following conditions mentioned in the equation 2

$$posprob_{w_i w_j} = prob(w_j|w_i) \text{where } 1 \leq i,j \leq pwc \text{ ...Eq.2}$$

Where pwc represents the positive word count and w_i, w_j represents the words

3.2.2. Neutral Prediction

Probability of the Neutral prediction on the set of the token on the reviews is identified on basis of the following conditions mentioned in the equation 3

$$neutprob_{w_i w_j} = prob(w_j|w_i) \text{ where } 1 \leq i,j \leq ntwc \text{......Eq.3}$$

where $ntwc$ represents the neutral word count

3.2.3. Negative Prediction

Probability of the negative prediction on the set of the token on the reviews is identified on basis of the following conditions mentioned in the equation 4

$$negprob_{w_i w_j} = prob(w_j|w_i) \text{ where } 1 \leq i,j \leq nwc \text{ .....Eq.4}$$

Where nwc represents the negative word count

3.3. Trust Computation

Trust computation to the classified review is processed using ensemble learning model on associating the behavioral features and contextual features. Those feature were obtained using the bidirectional feature representation model which incorporate the contextual knowledge and behavioral knowledge of the user using the BERT analysis.

3.3.1. BERT Analysis – Semantic features

BERT analysis employed to the word embedding vector to extracts the contextual and behaviour feature using the following process

- Sentiment base: Sentiment base composed of computation of lexicons to the word embedding vector and its corresponding sentiment polarity to the term.
- Modifier base: It estimates the sentiment variation to the different context.
- Semantic Rule base: Rule is applied to computes the sentiment of the user to various interests with rank.

Finally encoded vector is obtained to the word embedding vector on processing with transformer architecture.

3.3.2. Convolutional Neural Network

Convolutional Neural Network(CNN) [13] applied to process the encoded vector composed of the multiple contextual and behavioral feature to compute the trust of the review on processing it.

- **Convolution layer**

Convolution layer utilizes the kernel function to obtain the contextual features of the review and behavioral features of the reviews separately from the encoded vector. Convolution layer generates the feature map to the contextual features and behavioral features from the encoded feature vector on analysis with the domain knowledge.

Convolution C = kernel (Encoded feature Vector)

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Correlated (Encoded Feature Vector || Domain knowledge)

Low level feature $F_{c=}$ ($D_1(cw), D_2(cw)......D_n(cw)$)

$F_{c=}$ Feature map of contextual feature

Low level feature $F_{b=}$ ($D_1(bw), D_2(bw)......D_n(bw)$)

$F_{b=}$ Feature map of behavioral features

Feature Map F_m = Aggregation (F_b +F_c)

- **Max pooling layer**

In this layer, high level contextual and behavioral Feature are collected to the various contextual text vector and behavioral word vector. It uses the user preference vector to determine the correlation and covariance. Covariance matrix determines the low confidence and correlation determines the high confidences and it is considered as high level features.

Max pooling layer (Convolution feature map)

Covariance (Feature map with latent feature map of specified user)

High level Feature = { $H_1, H_2......H_n$}

Where H is the High level feature representing the low confidence and high confidence

Feature map (H)

The feature representations that can enhance the trust assessment of provided sentiment to the products using the hyper parameter values of the Fully Connected Neural Network is given in table 1.

Table 1: Hyper parameter of CNN architecture

Hyper Parameter of Scheduling Component	Parameter Values
Text Vector size	112
Learning rate	0.06
Sentiment Vector size	25
Number of Epoch	30
Error function	Cross entropy
Activation function	ReLu

- **Fully Connected layer**

The Fully Connected layer gathers the behavioral and contextual feature vector along the preference feature subset of the user through their inherent approaches which hierarchically abstract the latent features and learn the discriminative features of the user.

- **Softmax function**

Softmax function uses using the naive bayes classifier as it classifies the embedded vector into fake review classes and normal review through bayes rule. Bayes rule uses probability of the likelihood and prior to its posterior probability of the embedded features. It is give as

Probability evidence p(e) = P(Behavioral Feature) + P (Context feature) + P (Latent feature)

Resultant output the model is to classify the review as fake review and normal review on processing embedded vector on domain knowledge of the product domain as it yields various contextual information to various sentiments.

- **Loss Layer.**

This layer is to guarantee the high prediction accuracy on optimization of the hyper parameter of architecture layers. It reduces the reconstruction error among the various feature vector . Especially cross entropy is used as loss function to manage predicted feature vector against the over fitting and under fitting issues to its specified classes.

Algorithm 1: DCNN+BERT Pretrained Language model

Input: product review

Output: Fake and Normal review classes to the product review

Process

Pre-processing ()

S_w = Stop word removal (review sequence)

S_t = Stemming (S_w)

T = Tokenization (S_t)

Journal of Theoretical and Applied Information Technology
31st August 2025. Vol.103. No.16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

BERT Analysis (Word Token)
Compute contextual feature Set F_c & behavior feature Set F_b
Transformer()
Encode (contextual feature Set and behavior feature)
Encoded feature vector
Apply Convolutions Neural Network ()
Convolution layer ()
C = feature map (Encode feature vector)
Set Kernel () to Encoded Feature vector with Contextual aspect
Embedded Feature Map
Set Kernel () to Encoded Feature vector with behavioral aspect
Embedded Feature Map
Max Pooling ()
Compute weight to feature map context on user preference context
Fully connected layer ()
Normalize (feature map) feature
Activation Layer_ReLu(feature map)
Softmax (naive bayes)
Probability_Evidence (feature map _)
Class (Normal Review | fake Review)
Loss layer ()
Cross Entropy (confusion Matrix)

3.3.2. Recurrent Neural Network

Recurrent Neural Network(RNN) [13] applied to process the encoded vector composed of the multiple contextual and behavioral feature to compute the trust of the review on processing it. Recurrent Neural Network is represented as graphs for topological ordering as it efficient for inferring and learning the features. The topological ordering is used for activation propagation, and for gradient back-propagation of the encoded features for effective classification of the product reviews . The layers of the RNN composed of the hidden layers and output layer with activation and gradient function to process the feature towards achieving the effective classification results. Each layer has various properties to store and update the states of the feature. Finally features are illustrated in form of transition matrix as it is efficient in modifying the linear constraints.

- **Input layer**

Input layer represent the feature to neural network which is obtained from BERT model and it represents the initial states of the encoded feature vector and sub-vector with respect to various time stamp to the behaviour and contextual features.

- **Output Layer**

Output layer represents the target trust classes on processing the encoded feature on each layer. Further it specifies the desired activities to layers with set and subset of the feature vector on adding the error derivates to decrease the error in training and testing process. Table 2 defines the hyper parameter of RNN architecture.

Table 2: Hyper Parameter to the RNN

Hyper Parameter	**Values**
Text Vector Size	158
Model Learning Rate	0.001
Dimensions Size	65
Number of Epoch	50
Error function	Cross entropy

- **Abstraction layer**

Abstraction layer of the model is fine tuned with activation function to obtain the high level features from the encoded feature vector. It produces new state composed of high level features on optimizing old state with hyper parameters to produce the review trust classes on setting the reduced value to epoch.

- **Hidden Layer**

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Hidden layer represents the hidden vector containing encoded features processed in the abstraction layer along forget gate of LTSM architecture to compute the hidden feature to be stored in the particular cell state of the layer. The LTSM employs the activation function through sigmoid method in the forget gate for the feature collected in the input gate.

- **Activation function**

The learning rate of the RNN architecture is controlled and adjusted to the weights of the encoded features by implementing the sigmoid function. RNN architecture activation function is illustrated as many to one data structure to process the feature . Activation function is generated to initiate the output layer. Activation function is represented as

Sigmoid =tanh(optimal Features)

Sigmoid function is employed for analyzing the features for determining the patterns and defining the features to indicate their feature variation to generate the effective target classes.

- **Loss Layer**

This layer is to eliminate the overfitting and underfitting issue of the classification result. The classification accuracy of the architecture is enhanced on optimizing the hyper parameter of various layers of Recurrent Neural Network(RNN) to guarantee the reduced reconstruction error among hidden layer and abstraction layer.

Class C = Softmax(High Level features)

Further cross entropy is employed as loss function which is incorporated in the RNN architecture to control data seperability of class features. Hyper parameter of Recurrent Neural Network(RNN) is enhanced to obtain better results. Soft max function using optimal classifier is employed to the encoded features to obtain review trust classes.

Algorithm 2: RNN+BERT Pretrained Language model

Input: Food product review

Output: Fake and Normal review classes to the food product review

Process

Pre-processing ()

S_w = Stop word removal (review sequence)

S_t = Stemming (S_w)

T = Tokenization (S_t)

BERT Analysis (Word Token)

Compute contextual feature Set F_c & behavior feature Set F_b

Transformer()

Encode (contextual feature Set and behavior feature)

Encoded feature vector

Abstract learning ()

Calculate High Level Feature

Hidden Layer ()

Obtains the hidden feature along the extracted features vector through transition matrix

Forget Layer ()

Compute sparse feature using Forgot Gate function in the feature vector

Activation Layer ()

Employ Sigmoid Function to generate class on the feature extracted

Cross Entrophy Layer ()

Determine Cost Function for error derivates

Output Layer ()

Softmax operation of various constraints as desired level of the feature ()

Probability Evidence (feature map _)

Class (Normal Review | fake Review)

Loss layer ()

Cross Entropy (confusion Matrix)

3.3.3. Bidirectional Gated Recurrent Network

Bidirectional Gated Recurrent is evolution of the Recurrent neural network through gating mechanism. Gating mechanism is a long term short memory with reduced network parameters. Gated Neural Network uses encoded feature vector through reset gate and update gate. Gated recurrent Neural Network layer is as follows

- **Input layer :** Input layer obtains the encoded feature vector and constructs the hidden states to hidden layer.
  - Hidden layer : In this layer, Recurrent computation of the features is carried out. Hidden state is considered as vector which represents the memory of previous inputs. .
  - **Reset gate :** Reset gate is employed to compute the no of the hidden state to be forgotten on obtaining the previous hidden states to feature vector.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 3: Hyper Parameter of Gated Recurrent Neural Network

Parameter	Value
Vector size	130
No of neurons in the hidden state	50
Batch size	50
Epoch size	50
Learning rate	10^{-2}
Loss Function	Mean Square Error

- **Update gate :** Update gate is used to compute the no of activation vector to be incorporated into the new hidden state
- **Activation Vector :** Activation Vector is a considered updated feature vector of the previous hidden state that is reset by the reset gate
- **Output layer :** Output layer utilizes the final hidden state as input and produce the classification output

Algorithm 3: BGRNN+BERT Pretrained Language model

Input: product review
Output: Fake and Normal review classes to the product review
Process
Pre-processing ()
S_w = Stop word removal (review sequence)
S_t = Stemming (S_w)
T = Tokenization (S_t)
BERT Analysis (Word Token)
Compute contextual feature Set F_c & behavior feature Set F_b
Transformer()
Encode (contextual feature Set and behavior feature set)
Encoded feature vector
Apply Gated Recurrent Neural Network ()
Input layer ()
Initialize the hidden state with encoded feature vector
Hidden layer ()
Process the encode feature with hidden states
Reset State ()
Compute hidden state to be forgotten
update state ()
Compute activation feature vector to the hidden states
Output layer ()
Classifies the hidden state
Class (Normal Review | fake Review)
Loss layer ()
Mean square Error (confusion Matrix)

By combining these three architectures into an ensemble model, EDL-RNN+CNN+BiGRU, the proposed approach leverage the complementary strengths of each model. The ensemble model is more robust and effective in capturing the nuanced features of online reviews for sentiment analysis compared to using any single architecture alone. Weighted averaging is a common approach employed to ensemble learning to interface the predictions of individual architectures while assigning different weights to each model's prediction based on its performance.

4. EXPERIMENTAL RESULTS AND DISCUSSION

Experimental analysis of the ensemble model towards trust assessment to online product review is carried out in python environment using Flipkart dataset. In this 80% of the data are utilized for architecture training and 20% of the data are utilized for architecture testing. Confusion matrix uses the validation data and it provides True Negative (TN), False Negative (FN), True Positive (TP), and False Positive (FP). Those matrix values were used for following analysis

4.1. Dataset Description

In this section, dataset description of the various e commerce food review system is described with its attributes

- **Flipkart Dataset**

Flipkart review dataset is dataset composed of the various review of the product. In this work, opinion review collection is collected using web API through python programming on

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

establishing account. Dataset composed of 1.87 lakhs review during year from 2021 to 2023 on various food product reviews category in the geographical regions of India[25].

4.2. **Performance Metric**

In this section, performance evaluation of the learning model is enabled using the confusion matrix as it is capable of determining the efficiency and accuracy of the architecture. It is as follows

Precision is termed as the ratio of exactly identified positive observations on the encode feature vector to all of the expected positive observations on the encoded feature vector. In this analysis, proposed architecture provides better results to classify the encoded feature into fake review on analysis of different context on the text feature vector embedded and processed in the deep learning model. Figure 2 provides precision analysis

Precision = TP/TP+FP

4.2.1. Precision Analysis

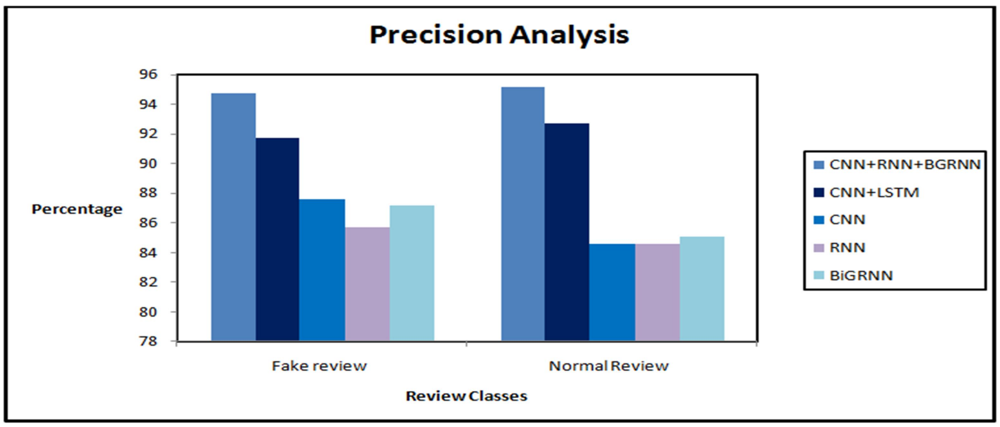

Figure 2: Precision Analysis

4.2.2 Recall Analysis

Sensitivity or Recall is termed the ratio of exactly identified positive observations on the encode feature vector to the over-all observations of encode feature vector. In this analysis, proposed architecture provides better results to classify the encoded feature into fake review on analysis of different context on the text feature vector embedded and processed in the deep learning model. Figure 3 provides recall analysis

Recall = TP/TP+FN

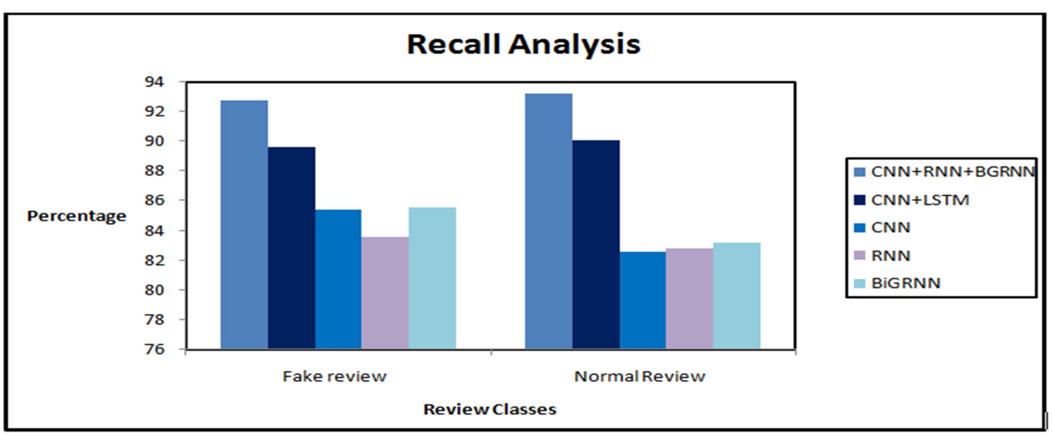

Figure 3: Recall Analysis

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4.2.3. F Measure Analysis

F - measure is mentioned as the weighted average of Precision and Recall. As a outcome, it utilizes false positives and false negatives parameters of the confusion matrix. In this analysis, proposed architecture provides better results to classify the encoded feature into fake review on analysis of different context on the text feature vector embedded and processed in the deep learning model. Figure provides F measure analysis

F1 Score = 2*(Recall * Precision) / (Recall +Precision)

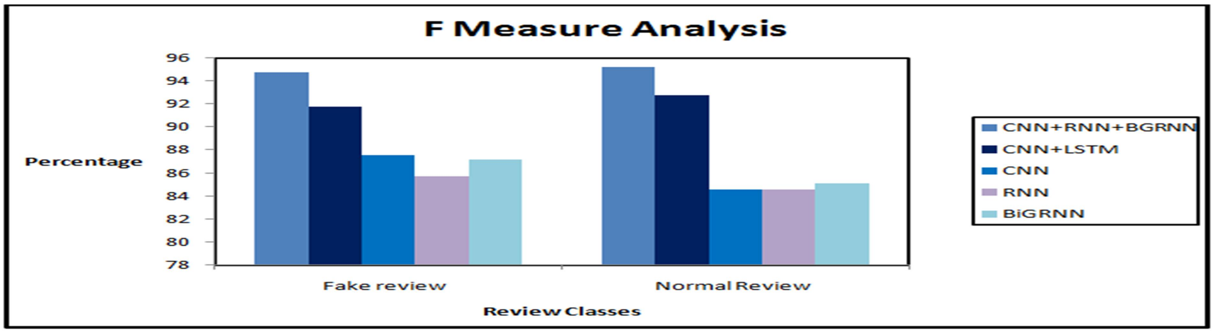

Figure 4: F Measure Analysis

Finally, fake review classes detected using proposed ensemble architecture exhibits better performance compared to state of art approaches. In particular, BERT analysis produces better semantic feature and deep learning model extract the different context feature to produce better accuracy in classifying the fake reviews. Table 2 provides the performance evaluation results of the trust assessment architectures.

Table 2: Performance Analysis Of The Trust Assessment Deep Learning Models

Technique	Trust Classes	Precision	Recall	F measure
CNN+RNN+BGRNN	Normal	95.2	93.2	95.8
	Fake	94.8	92.8	94.9
CNN+LSTM	Normal	92.8	90.5	92.9
	Fake	91.8	89.5	91.9
CNN	Normal	84.6	82.7	84.8
	Fake	87.6	85.9	87.8
RNN	Normal	84.6	82.4	84.9
	Fake	85.7	83.8	85.9
BGRNN	Normal	85.1	83.5	85.6
	Fake	87.2	86.1	87.8

5. CONCLUSION AND FUTURE WORK

In this work , ensemble deep learning model composed of the Recurrent Neural Networks (RNN), Improved Pooling based Convolutional Neural Networks (IPCNN) and Bidirectional Gated Recurrent Units (BiGRU) is designed and implemented using online product review from users of the Flipkart. Initially, preprocessing steps such as stop word removal , special character removal , stemming and tokenization is carried out to reduce the computational challenges. Preprocessed model is projected to the n-gram model to compute the contextual and behaviour features from the token with semantics. Obtained feature is encoded in the transformer model and transformed to ensemble model for review trust computation and class generation. Experimental and performance analysis of the ensemble model produces 94.2% of accuracy, 94% of precision, 93% of recall in trust computation of the online product reviews. As a future work, incorporating the attention network for processing the features or token with respect to domain knowledge and behaviour aspects will results in better outcomes.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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