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RESEARCH ARTICLE

Analyzing Public Sentiment on the Amazon Website: A GSK-Based Double Path Transformer Network Approach for Sentiment Analysis

LELLA KRANTHI KUMAR[1], VENKATA NAGARAJU THATHA[2], PAMULA UDAYARAJU[3], D. SIRI[4], G. UDAY KIRAN[5], B. N. JAGADESH[1], (Senior Member, IEEE), AND RAMESH VATAMBETI[1]

[1]School of Computer Science and Engineering, VIT-AP University, Vijayawada 522237, India
[2]Department of Information Technology, MLR Institute of Technology, Hyderabad 500043, India
[3]Department of Computer Science and Engineering, Sagi Rama Krishnam Raju Engineering College, Bhimavaram 534204, India
[4]Department of Computer Science and Engineering, Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad 500090, India
[5]Department of CSE (AI and ML), B. V. Raju Institute of Technology, Narsapur 502313, India

Corresponding author: Lella Kranthi Kumar (kranthi1231@gmail.com)

ABSTRACT Sentiment Analysis (SA) holds considerable significance in comprehending public perspectives and conducting precise opinion-based evaluations, making it a prominent theme in natural language processing research. With the increasing trend of online shopping and social media usage, there is a constant influx of diverse data types such as images, videos, audio, and text. Notably, text stands out as the most crucial form of unstructured data, demanding heightened attention from researchers. Given the voluminous nature of data, various methodologies have been proposed to effectively mine big datasets for valuable insights. The challenge of accurately identifying polarity in extensive customer evaluations persists due to the intricacies associated with handling large textual datasets derived from reviews, comments, tweets, and posts. This study addresses this challenge by presenting a straightforward architecture, the Double Path Transformer Network (DPTN), designed to model both global and local information for comprehensive review categorization. To enhance the synergy between the attention path and the convolutional path, the study advocates a parallel design that combines a robust self-attention mechanism with a convolutional network. The research employs the gaining-sharing knowledge optimization (GSK) approach to fine-tune hyperparameters, thereby improving the model's classification accuracy. Additionally, the investigation demonstrates that optimization algorithms and deep learning collaboratively manage class imbalances with finesse, even in the absence of explicit measures for such concerns. In the experiment analysis of the proposed model ultimately achieved an accuracy of 95.

INDEX TERMS Amazon review, double path transformer network, gaining–sharing knowledge optimization, sentiment analysis, unstructured data.

I. INTRODUCTION

A. BACKGROUND OF SENTIMENT ANALYSIS

Since the dawn of civilization, the art of communication has been fundamental to strengthening interpersonal bonds. Social media has developed into an effective instrument for networking, and as a result, almost every part of society uses it nowadays [1]. Online marketplaces make up the bulk of social media. The majority of consumers now choose to shop online due to the fast expansion of e-commerce knowledge. Depending on the customer's experience, people can use social media to offer positive or negative feedback on a variety of circumstances, items, and resources. Because they help enhance the services, negative remarks are crucial to

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the company's success. Sentiment analysis is useful in this context [2].

By analysing the tone of reviews written about various products, sentiment analysis helps to reveal how customers feel about these items. Sentiment analysis is typically performed at three levels, according to various research studies: sentence-level, document-level, and phrase-level [3]. The process of sentiment analysis is illustrated in Figure 1, with its sub-stages.

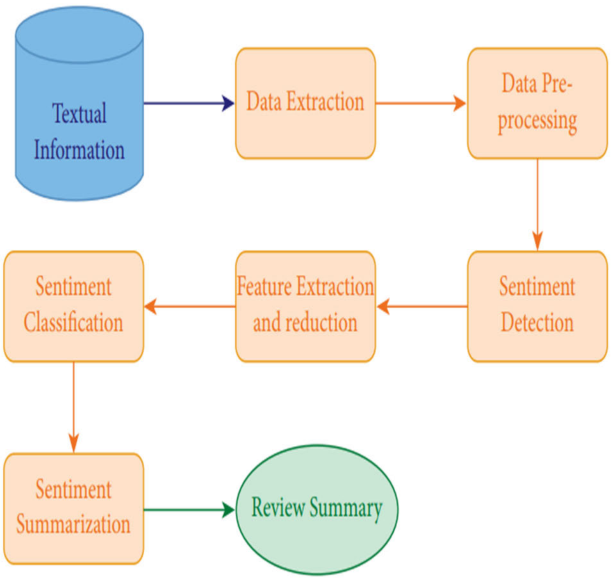

FIGURE 1. Sentiment analysis's stages.

B. IMPORTANCE OF REVIEWS IN SENTIMENT ANALYSIS

Research into people's thoughts, feelings, attitudes, and emotions is known as sentiment analysis. According to [4], it's one of the hotspots for NLP research. The field of data mining has been extensively researched. Hence, this study has expanded beyond the realm of science to encompass the fields of management and social science. As platforms like Twitter, microblogs, and chat rooms continue to grow in popularity, sentiment analysis is becoming an increasingly important tool [5]. Now, more than ever before, a vast quantity of opinions can be collected and analyzed digitally. Opinions are fundamental to all human endeavors, which is why sentiment analysis technologies find widespread usage in both commercial and non-profit sectors. As a result, they have a major impact on how we act [6]. Everyone else's views and values shape our worldview, which in turn influences our beliefs, perceptions, and choices. It is for this reason that people frequently ask for other people's opinions when a decision needs to be made [7]. Both people and businesses can benefit from this. Customers rate and review items on Amazon. The purpose of these reviews varies from product to product, but generally speaking, they help businesses improve their offerings and draw attention to those that have received unfavorable feedback [8].

The expansion of the internet is influencing the business sector since it speeds up the flow of information. Some customers will share their thoughts about a product they've purchased on review sites or social media [9]. Among the many internet marketplaces, Amazon.com stands out. To handle massive amounts of text, an opinion engine is required. The process of sentiment analysis makes use of the text mining technique. Through the processing and analysis of massive amounts of data, text mining enables the uncovering of previously unseen information or trends [10]. They state that text mining is able to help with problems like processing, organizing, grouping, and analyzing massive volumes of unstructured material. Classification is one mining technique.

C. ADVANCED ARTIFICIAL INTELLIGENCE TECHNIQUES FOR SENTIMENT ANALYSIS

An ever-growing role for machine learning in sentiment analysis has emerged within the last decade [11]. There has been a meteoric rise in the application of sentiment analysis with the introduction and development of deep learning procedures. Lack of clearly defined confidence metrics for predictions made by such methods is a mutual matter in machine learning [12], making it impossible to determine where in the review (feature) space trustworthy predictions can be anticipated.

In the group of confidence predictors, conformal prediction offers a structure that lets data be shared, which lets very specific confidence measures be used at the instance level [13]. It is important to note that conformal prediction does not add any additional requirements when creating confidence predictors because all machine learning methods typically assume exchangeability or, more frequently, that the data is IID (Independent and Identically Distributed) [14].

Using the word vector network, nearly 5.2 million reviews from the following categories were analyzed for sentiment on Amazon: beauty, books, electronics, and home [15]. This was done in conjunction with density-based conformal prediction, and one of the three datasets studied was the 50k IMDb review dataset, which is well-balanced (1:1).

D. MOTIVATION OF THE RESEARCH WORK

In response to the increasing demand for SA, businesses and organizations are focusing on improving their public relations, launching campaigns, strengthening their weak spots, and expanding their clientele. Feedback from consumers regarding a company's goods and services is highly valued [16]. In addition, political groups like to know how the general public perceives them and how the media covers them. These days, SA is more concerned with deciphering the feelings conveyed in reviews posted on social media. Many fields have begun to adopt SA, including those dealing with harassment, politics, entertainment, sports, and even medicine [17].

Current research topics in SA include better natural language processing (NLP) methods, data mining for predictive investigation, and text contextual comprehension [18]. It has been common practice to employ support vector machines (SVM) to address various NLP issues for quite some time. Neural network (NN) techniques built on dense vector illustrations have lately attained state-of-the-art presentations in various NLP-related applications [19]. In their early days, deep learning NNs showed great promise in tasks involving pattern recognition and computer vision. This development has algorithms for handling complex NLP tasks like sentiment analysis.

E. CONTRIBUTION OF THE STUDY

When the system's developers realized how crucial sentiment analysis was for online life, they set out to improve the process. In terms of computer complexity, the proposed strategy yields the same or better outcomes with the highest level of certainty and the lowest amount of effort expended [20]. The study has looked into how different preprocessing steps, like cleaning and normalizing the data, removing hashtags and punctuation, changing the text to lowercase, and tokenizing, affected customer reviews. The research in this paper employs optimized deep learning methods to examine customer reviews on Amazon.

- At first, data is retrieved from Amazon.com and subjected to a series of pre-processing procedures in order to clean it up.
- The characteristics are formed from the pre-processed texts using various word embedding approaches.
- The research suggests a hierarchical dual-path backbone to enhance review detection performance by giving CNN global attention.
- We suggest a straightforward yet efficient solution called a bidirectional connection module that allows two parallel ways to communicate context information.
- Without utilizing complicated and computationally intensive modules, the entire model produces features that are robust to scale through the use of a multi-head attention block during the concentrating phase.
- At last, the study was assessed using various metrics, including precision, recall, accuracy, and F1-score, in conjunction with pre-existing methods.

F. PAPER ORGANIZATION

Section I begins with a brief overview of sentiment analysis and its significance before moving on to review classification. Section II provides a comprehensive analysis of current models along with their limitations. Section III provides the study materials, while Section IV provides a brief clarification of the suggested model. As promised in Section V, here is the experimental data to back up the effectiveness of the suggested model. Section VI concludes with a demonstration of future work.

II. RELATED WORK

A convolutional neural network (CNN) model for negative/positive sentiment classification in text reviews has been provided by Qorich and El Ouazzani [21]. To find the best model, we also compared our suggested CNN model with other models' word embedding representations. Using the Amazon reviews dataset, the tests show that several model designs can obtain acceptable performances. Results show that stop-words should be included in sentiment analysis tasks; removing them can lead to a wrong prediction of sentiment. In practice, compared to the CNN model that didn't use stop words, the one that did saw an improvement of 2% in accuracy. Additionally, we proved that on large-scale datasets, using a random initialization method outperforms supervised and embedded model vectors. The model can learn more accurate features with less computational effort after training the word embedding representation. In addition, our CNN model outperformed the baseline ML and DL approaches, and we increased CNN accuracy to 90% on the Amazon reviews dataset.

Researchers Vollero et al. [22] set out to use social media comments made by Amazon customers to determine what factors most influence the company's stock price. Using NLP-based methods, they analyzed the content and sentiment of user comments extracted from the Facebook pages of three major Italian retailers over the course of two years (2016-2018) to determine the extent to which these retailers' service attributes were associated with Amazon-related customer dissatisfaction. Consumers have a lot to say about the impact of Amazon on retailers of consumer electronics, particularly in the areas of pricing, service, in-store personnel, and after-sale assistance. Consumers' unfavorable views in Facebook comments, when compared with similar assessments on the Italian Amazon website, indicate that Amazon's service standards have increased consumer expectations and decreased consumer satisfaction when interacting with other businesses. Beyond the commonly recognized determinants of price and logistics, they propose additional study to elucidate Amazonification in terms of customer impatience and discontent more broadly.

The goal of the research by Venkataraman and Jadhav [23] was to analyze customer reviews of mobile phones, categorize them into different star ratings, and then find out how accurate the ratings were in expressing the mood. This could only be accomplished once the data had been cleansed and pre-processed. The TF-IDF approach and word embedding were then used to convert the text into numerical numbers. Ultimately, various methods such as Support Vector Machines, Logistic Regression, and Ensemble models were employed, and the accuracy of their performance was studied. A number of criteria are utilized for evaluation, including recall, accuracy, precision, and the F1-Score. On a balanced classifier with Unigram performs better.

A unique hybrid recommender system has been proposed by Elahi et al. [23] that can analyze reviews and extract feelings to use in making recommendations. To provide suggestions for those who can add extra data, like the review sentiment, they deployed sophisticated algorithms. In several cases, such as the music industry, they found no strong correlation between the ratings and the sentiments expressed in user evaluations. As a result, sentiment may serve as an additional indicator of user input, revealing a new facet of consumer preferences. To evaluate the effectiveness of their suggested hybrid recommender system, they have taken into account both star ratings and review sentiment. For this study, they used two popular datasets—Amazon Digital Music and Games—and demonstrated that the suggested hybrid recommender system outperformed several baselines. Two evaluation scenarios were used to make the comparisons: one where the ratings were taken as user feedback and the other where the review sentiments were used as user input.

To recover the rating matrix and aid in recommendation, Liu and Zhao [24] provide a sentiment analysis and matrix factorization (SAMF) based recommendation system. This system employs deep learning technologies and topic models to fully mine the implicit information in reviews. First, LDA (Latent Dirichlet Allocation) is used to construct user topic distribution from reviews, which comprise both user reviews and item reviews. On the basis of topic likelihood, the user feature matrix and object feature matrix are generated. The second step is to combine the user feature matrix with the item feature matrix to form a user-item preference matrix. In the third step, the user-item rating matrix is created by integrating the original rating matrix with matrix. Lastly, the user-item rating matrix is updated and modified using BERT (Bidirectional Encoder which quantifies the sentiment info in the reviews and integrates it with the rating matrix. Lastly, rating prediction and Top-N suggestion are accomplished using the updated user-item rating matrix. Results from experiments conducted using Amazon datasets show that the suggested SAMF outperforms other traditional algorithms when it comes to suggestion performance.

In their publication, Jin et al. [25] introduced the Amazon-M2 Multilingual Multi-Locale Shopping Session Dataset. With millions of user sessions across six countries and languages, this dataset is the first of its kind. English, German, Italian, and Spanish are the most common product languages. Surprisingly, the dataset can aid in improving personalization and understanding of user preferences, which in turn can enable new activities and improve existing ones. This work introduces three tasks: next-product title generation—to assess the possibilities of the dataset. By completing the aforementioned tasks, we are able to compare various algorithms on our suggested dataset, which allows us to gain valuable insights for future studies and applications. The KDD CUP 2023 competition we ran, which was based on the suggested dataset and challenges, also had thousands of entries.

As recommendations to users, Lakshmi and Bhavani [26] have provided the top k links predicted by link prediction measures. At first, they modify various preexisting link prediction methods and apply them to the recommendation issue. A recommendation framework based on the problem in social networks is proposed as the main contribution of this work. This framework makes use of incorporates temporal data that is available on existing links. We test the suggested method on three different datasets: one from MovieLens, one from Epinions and Amazon, and one from TripAdvisor, which contains ratings for hotels. When it comes to enhancing recommendation quality, the results reveal that link prediction techniques based on temporal probabilistic info work better. Regarding Movie Lens, Epinions, TripAdvisor, and Amazon specifically, the area under the ROC curve (AUROC) is improved by 10%, 23%, 17%, and 9% respectively, as compared to the usual item-based collaborative filtering method using the temporal cooccurrence probability measure. Area under Normalized Rank-Score both show comparable enhanced performance.

Using the Transformer Perfect—a deep learning perfect that effectively integrates textual and utility matrix info—Ho et al., [27] have projected a new approach. In order to get the most out of the Transformer model, the research recommends feature extraction strategies that are well-suited to each data source. With a reduction ranging from 10.79% to datasets, the experimental results show that the suggested model considerably enhances recommendation accuracy when associated with the baseline for the metric. The suggested model also reduces the MAE measure by 34.82% to 56.17% for the Amazon sub-datasets in comparison to SVD, widely recognized as one of the best representations for recommender systems. With improvements in Precision of up to 108%, MAE of up to 65.37%, and RMSE of up to 59.24%, our suggested model surpasses the graph-based model in terms of performance. Results from experiments conducted on Amazon datasets further show that our suggested strategy outperforms a model that just relies on utility matrix data by incorporating information from textual sources.

Concerning user behavior data in FedRecs, Yuan et al. [28] have investigated the privacy concern. To be more precise, we conduct the initial comprehensive investigation into assaults on FedRecs that aim to infer membership at the interaction level. After designing an attacker that targets interactions through membership inference, the protection mechanism known as Local Differential Privacy (LDP) is used to counter this attack. Unless recommendation performance is severely impaired, actual research reveals that LDP is ineffective against such novel threats. We develop a straightforward defense mechanism to lessen the impact of interaction-level membership attacks by lowering the attacker's inference accuracy while maintaining recommendation presentation. The efficacy of our solutions is demonstrated by extensive trials carried out with two popular datasets.

For improved recommendation quality, Hiriyannaiah et al., [29] have taken data sparsity into account using a new neural CF-based DeepLSGR model. It is a bidirectional model that uses user-submitted text reviews to forecast ratings and then makes recommendations based on those predictions. The model's hidden layers include (LSTM) and Gated Recurrent Units (GRU). Its performance in studies using the

OpinRank and Amazon Fine Food Reviews datasets was 97% accurate, 61% recall, and 0.87 RMSE. By comparing it to previous works, it is clear that DeepLSGR offers better recommendations.

To overcome the issue of data distortion caused by sparsity, Kuo and Li [30] used the particle swarm optimization method (PSO) to find the optimal similarity of customer ratings. In addition, the features of customer feedback were extracted using representations from transformers (BERT). Lastly, the PSO was used to mix the features of various data kinds and find the right weight matrix. If rating and review data were combined, recommendation performance may be significantly enhanced. Furthermore, the suggested approach surpassed multiple prior approaches in terms of mean squared error and mean complete error when tested on six Amazon datasets.

The collaboration Variational Graph Auto-Encoder (CVGA) is a new end-to-end graph recommendation model projected by Zhang et al., [31]. It encodes user-item collaboration interaction bipartite graph using the info propagation and aggregation principles. Instead of learning user or item embeddings, these associations are used to infer the probability distribution of user behavior for parameter estimation. In doing so, we make a plausible and elegant reconstruction of the full user-item interaction graph rendering to the known probability distribution. Looking at it through the lens, we can solve the graph recommendation task with almost linear time complexity by transforming it into a graph creation problem. We show that CVGA can be trained quicker than state-of-the-art baselines for tasks while retaining comparable performance across four datasets. Additional research confirms that CVGA is capable of solving the data sparsity issue and works just as well with massive datasets.

A new method that uses LLMs to build personalized reasoning graphs has been proposed by Wang et al., [32]. To reflect the user's interests in a way that can be understood, these graphs connect their profile with their behavioral sequences using causal and logical deductions. Chained graph reasoning, knowledge base self-improvement makes up our technique, LLM reasoning graphs (LLMRG). In order to enhance traditional recommender systems, the resulting reasoning is encoded networks; this process does not necessitate any new information about users or items. Our method shows how LLMs can make personalized reasoning graphs that enable recommender systems to be more rational and interpretable. Recommendations can take advantage of LLM-derived reasoning graphs and constructed recommendation systems with LLMRG. On both benchmarks and real-world scenarios, we show that LLMRG improves base recommendation models.

A new method for recommendation based on the semantic awareness of HIN embeddings, SemHE4Rec, was proposed by Pham et al., [33]. To learn user and item representations in HIN efficiently, we offer the SemHE4Rec model, which includes two embedding approaches. Then, the matrix factorization (MF) procedure is made easier with these user representations that are rich in structural details. To begin, there is the time-honored method of co-occurrence representation learning (CoRL), which seeks to understand the frequency with which users' and things' structural characteristics occur together. By means of meta-paths, the linkages between these structural elements are depicted. Specifically, we use the heterogeneous Skip-gram architecture and the famous walk approach to achieve this. The second way for embedding is an SRL approach, which stands for semantic-aware representation learning. The recommendation task's focus is the primary focus of the SRL embedding technique. Lastly, in order to complete the recommendation task, all of the learned user and item illustrations are integrated with the extended MF and optimized together. In contrast to the state-of-the-art recommendation techniques that use HIN embedding, the proposed SemHE4Rec performs well on real-world datasets. The experiments also show that combining representation learning improves recommendation performance.

Lastly, the literature research reveals that there are numerous obstacles impacting the effectiveness and accuracy of sentiment analysis and social media content evaluation.

III. MATERIALS AND METHODOLOGY

A total of twelve groups consisting of five-core product appraisals retrieved from Amazon.com (Table 1) [34], [35] comprise the data utilised in this study. The old grading system that used numbers from 1 to 5 was changed to a binary system that used the numbers 1-2 for negative and the numbers 3-5 for neutral and positive. The imbalance ratios of all datasets range from around 6.7:1 to 17.4:1, indicating that they are significantly lopsided (Table 1).

A. DATA PRE-PROCESSING

Text data analysis relies heavily on data pre-processing [36]. Tweets, blogs, reviews, and other forms of textual content might have repeats and redundancies, which can make text data more complex. The study has looked into how different preprocessing steps, like cleaning and normalizing the data, removing hashtags and punctuation, changing the text to lowercase, and tokenizing, affected customer reviews. Data pre-processing is a filtering procedure that is used in data normalization. For instance, data pre-processing may involve normalizing the data, tokenizing words, eliminating stop words, padding, and excess spaces, transforming text data to lowercase, and removing hash tagging. The data in the necessary format was achieved through the implementation of numerous tasks in this job.

1) ERASE PUNCTUATION

Between forty and fifty percent of every given piece of written text is punctuation. The results of any sentiment analysis model are unaffected by punctuation. These punctuations are completely irrelevant to the sentiment analysis, so it is crucial that you eliminate them. Here, we displayed the statistics in their normalized form after removing any punctuation

TABLE 1. Dataset characteristics.

		Training set[a]							Test set		
Category	Successful[b]	Class unbiassed and positive number of reviews	Class neg number of reviews	Percentage of class negative reviews	Class negative median words/ review	Class neutral and positive Median words/ review	Class neutral and optimistic number of reviews	Class negative of number reviews	Percent age of class negative reviews	Class negative median words/ review	Class neutral and positive middle words/ review
cds_and_vinyl	yes	954,874 (375,5601)	76,341 (19,648)	7.4 (5.0)	105 (76)	99 (44)	39\3,054	13,2\94	3.3	36	13
books	yes	11,656,232 (9,191,149)	1,001,745 (692,288)	7.9 (7.0)	88\ (69)	62 (49)	13,60\1,15 9	828,64\\3	5.7	46	36
electronics	yes	2,268,955 (1,906,881)	311,990 (248,8661)	12.1 (11.5)	75 (67)	52 (46)	3,6299964	455,27\8	11.1	42	22
office_products	yes	202,853 (185,812)	18,947 (16,190)	8.5 (8.0)	70 (63)	42 (39)	507,459	34,864	6.4	39	17
cell_phones_and_acc essories	yes	276,950 (269,914)	41,077 (39,370)	12.9 (12.7)	45 (44)	37 (36)	709,108	97,290	12.1	32	21
sports_and_ outdoors	No	694,7924 (667,185)	57,191 (54,142)	7.6 (7.5)	57 (55)	43 (42)	1,846,242 5	149,287	7.5	36	22
grocery_and_ gourmet_food	No	31277,867 (285,490)	29,125 (26,034)	8.5 (8.4)	55 (53)	40 (38)	695,311	59,874	7.9	31	17
arts_crafts_and_ sewing	No	109,150 (107,346)	6,265 (6,118)	5.4 (5.4)	50 (49)	32 (31)	323,548	18,922	5.5	33	15
clothing_shoes_ and_ jewelry	No	2,119,165 (2,069,843)	225,723 (220,110)	9.6 (9.6)	41 (41)	34 (3\4)	7,810,225	873,00\5	10.1	27	19

[a]Values in parenthesis are for dated 2011– 14 only.
[b]Deep learning/Conformal Forecast perfect positively built (yes) or not (no).

from the text. The resulting text is condensed and made easier to understand. The input data was stripped of any punctuation.

2) CONVERT THE TEXT DATA TO LOWERCASE

Customers post content in reviews that doesn't adhere to standard grammar rules; for example, the text has both lowercase and uppercase letters. The study makes extensive use of approaches that are responsive to specific cases. Consequently, the classifier struggles to identify the text's polarity. If the entire text is formatted according to industry standards, this problem should go away. In contrast, the lower (txt) statement is utilized when the same procedure is to be executed manually. It changes all capital letters to lowercase while keeping all other characters in their original forms. Changing all capital letters to lowercase is demonstrated in the following example: One possible way to lowercase ''I Am A Senior Big Data Analyst in Islamabad'' is to say ''I am a senior big data analyst in Islamabad.''

3) TOKENIZATION OF THE TEXT

Tokenization is a method for segmenting text streams into smaller pieces of text, such as phrases. Tokens consist of broken bits of text. The goal of this method is to simplify difficult textual topics. When tokens are used, data mining gets easier. Semantics and sentiment analysis both benefit from tokenization, and lexical evaluation relies heavily on it. An integral part of the natural language processing pipeline is tokenization. The study will not be able to begin model creation unless the text is cleaned properly. Word tokenize and phrase tokenize are the two subsets of tokenization. This formatted data can be used for:

- Count the number of words in the text.
- Determine the word frequency. At this point, the text data is broken down into words. Miniature word or symbol packets are created from a huge and complicated record. For instance, ''I am a data analyst in Islamabad'' is one possible tokenization of the aforementioned text.

4) REMOVAL OF STOP WORDS

Text files often contain repeated words. Consequently, removing the stop words is of the utmost importance. The use of stop words never adds value to anything written. Words of this type tend to appear frequently in written works. This selected data has the stop words removed from it. This method improves system efficiency while reducing textual content.

5) REMOVAL OF THE HYPERLINK

Links have lost all significance in any database. The connections are only useful in a functional sense. To refine the text's polarity, the study exclusively uses tweets, comments, and reviews as representations of ideas and feelings based on the gathered data. Therefore, removing the links from the databases is of the utmost importance.

6) REMOVAL OF HASH TAG

Additionally, hash tagging is quite trendy right now. Hashtags are frequently used in customer feedback. Hashtags take up a lot of space. When it comes to sentiment analysis, hashtags don't work. For the classifiers, these simply increase the level of uncertainty. Therefore, it is absolutely necessary to eliminate hashtags. The training data is made more concise and obvious by removing the hashtags from the datasets.

7) REMOVAL OF UNNECESSARY SPACES

Additionally, hash tagging is quite trendy right now. Hashtags are frequently utilized in customer feedback. A lot of space is consumed by hashtags. When it comes to sentiment analysis, hashtags don't work. For the classifiers, these simply increase the level of uncertainty. Therefore, it is absolutely necessary to eliminate hashtags. The training data is made more concise and obvious by removing the hashtags from the datasets.

8) PADDING

The classifier has a hard time with sentiment analysis because the consumer review databases have both very brief and very lengthy reviews. The sum of pixels that are added to the review when the network evaluates it is known as CNN-related padding. Padding is just a few zeros added to the end of our input review to make sure every customer review is the same length.

9) POS TAGGING

Classifying training data words according to their predetermined grammatical form is the goal of POS. This group takes word meaning into account. Putting labels on point-of-sale systems is no picnic. While point-of-sale labeling can't fix the severe discovery problem in opinion analysis, it helps a lot with many other issues. This procedure gathered several viewpoints and aspects for a product review. To define a specific feature, one uses the altered POS tagger. The review gives users access to the grammar relations-provided POS tagging mechanism. To establish the speech part of the examination, utilize In addition, POS tags identified appropriate substantive and substantial potential problems. The observable output is generated in this POS process by means of a concealed Markov model (HMM), whereby tags are concealed. Finding a mathematically optimal tag sequence (C) is always the goal when POS is tagging.

$$P(C|W) \tag{1}$$

where C denotes $C1, C2, C3, \ldots, CT$, and W denotes $W1, W2, W3$, and WT.

B. FEATURE EXTRACTION USING WORD EMBEDDING

A neural word-to-vector model, Word2Vec [37], predicts the vector of a needed word by using its surrounding words. The Word2Vec embedding model typically makes use of two learning strategies: skip-gram and CBOW. The CBOW method uses the current word to bridge the gap between context words; therefore, it doesn't change the sequence of nearby words, in contrast to the skip-gram strategy, which prioritizes nearby words over faraway ones. Using solely local context, CBOW and skip-gram both learn mutual vector representations for every word.

In contrast to Word2Vec, GloVe [38] neural word embedding takes the full context of words into account. In the GloVe word embedding, a neural network is employed to decompose a matrix into a word vector. Because the GloVe embedding model takes into account the association among word pairs and provides additional meanings to the neural network, it outperforms Word2Vec [38] in word resemblance and analogy tests. The weights of common word pairings, including "the" and "a," are decreased via GloVe embedding as well. On the other hand, a co-occurrence matrix—the foundation of the GloVe model—requires a substantial amount of memory for storage purposes.

Since learning is a shared difficulty, FastText [39] follows Word2Vec's approach of learning the vector of each word together with the n-grams inserted within each word. The next stage in training is to create a single vector by averaging the representation values. Neural word embedding can encode substantial sub-word info using these models, although GloVe. When it comes to neural word embedding models, FastText is light years ahead of Word2Vec.

Transformer bidirectional encoder representations; the acronym is BERT [40]. By conditioning the right and left context at all levels, BERT aims to bidirectional representations from unlabeled data. For this reason, it is possible to train a pre-trained BERT model for tasks, including sentiment investigation, question answering, and language translations. No major changes to the design are required with this method. When put into practice, BERT is both simple and effective.

IV. PROPOSED METHODOLOGY

A. CONSTRUCTION OF THE PROPOSED NETWORK

Figure 2 depicts the structure of the model that we have suggested. A backbone with Transformer enhancement,

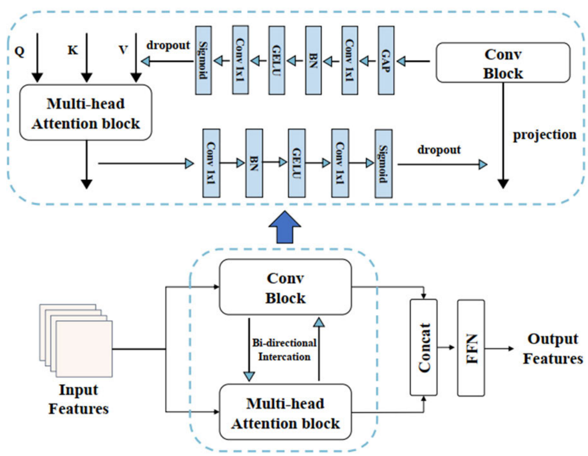

FIGURE 2. The block for the hybrid transformer.

an attention decoder head with several heads, and a post-processing algorithm make up the pipeline.

The research uses a dual-path approach to integrate self-attention and convolution. By handling (FFN) for feature output, it tries to gather information within and across initial receptive fields. Initially, following the conventional CNN backbone model, the input data is passed through an FPN assembly to derive multi-level features. This structure consists of four stages, each with a different downsampling rate: f4, 8, 16, 32g, and so on. The second step is to use multi-head attention to extract after upsampling the extracted features to the same scale. Two maps—one for likelihood and one for threshold—will be created using the feature.

B. MATHEMATICAL DESIGN OF THE PROPOSED NETWORK

1) TRANSFORMER-ENHANCED BACKBONE

The study can logically make CNN and Transformer operate in tandem to achieve greater performance since they each have their own limits and complementary advantages. Convolutional layers are able to model local relations due to their inductive bias. Following prior research [41], a 4×4 window is utilized, as shown in Figure 2. Our goal is to maximize efficiency in the CNN path by applying depth-wise size. Also, we need to change the number of channels so they align with the merged branch, allowing them to be seamlessly integrated because the two paths are architecturally different. Their outputs are combined after the channel adjustment and normalized using separate normalization layers. By optimizing both parallel branches at the same time during training, we can achieve stronger feature representation learning by weaving features across the two branches. Then, the final output features are generated by fusing the learned relations in both routes using a consecutive Feed Forward Network (FFN).

2) FEATURE INTERACTION MODULE

Figure 2 shows that there are bidirectional interactions between the output features of dual-path branches, and that these features are not merely concentrated. Better representation learning in both branches can be achieved with the help of the complementary clues provided by the parallel branches. As one route uses attention to extract channel/spatial context, the other route uses channel/spatial interaction to do the same. The channel and spatial interactions make up the bidirectional interactions within the same block. To begin with, the research utilizes a layout that is comparable to the SE layer [42], meaning that data from the convolutional branch is transferred to the other branch via the channel interaction. This structure includes a single GAP layer, two layers that are connected with normalization and activation, and provide a dynamic weight to various channels. The channel sum is reduced to 1 using info from the branch by means of two consecutive 1×1 layers that interconnect with BN and GELU. Additionally, a sigmoid layer is utilized for the distribution of spatial weights.

3) HYBRID TRANSFORMER BLOCK

An efficient parallel architecture, a FFN network make up the hybrid Transformer block [43]. We also present residual connections, which are defined in the following way:

$$\hat{X}_i = Concat(LayerNorm(X_i), MSA(X_i), CONV(X_i) + X_i) \tag{2}$$

$$X_{i+1} = FFN(LayerNorm(\hat{X}_i) + \hat{X}_i) \tag{3}$$

where X_{i} where Conv is the depth-wise convolution process, MSA denotes the attention branch, and represents the features at the i^{th} block.

4) MULTI-HEAD ATTENTION DECODER

In order to combine data from several scales, the majority of semantic segmentation algorithms employ summing up or cascading techniques. But paying little attention means that such a basic fusion paradigm would necessarily miss some crucial elements. Thus, in order to re-attend to the cases while maintaining the honesty of the spatially hidden text region, the study employs a multi-head attention decoder.

The study scales the features from diverse stages into the similar resolve first so that they can be treated at the similar scale. The study denotes the feature maps made from the four phases in our backbone as $X \in R^{N \times C \times H \times W} = \{X_i\}_{i=0}^{N-1}$, where N is equal to 4. The study uses intermediate feature $S \in R^{C \times H \times W}$. The features are then divided into N pieces along the channel dimension using a basic but effective multi-head attention module [44]. In this case, N is 4. In order to obtain the final fused feature F, the relevant scaled features will be given the data dependent dynamic weights. One way to express the aforementioned procedures is as:

$$\hat{F} = Conv(Concat\ ([X_0, X_1, X_{N-1}])) \tag{4}$$

The research uses a dual-path approach to integrate self-attention and convolution. By handling input sending signals to the Feed-Forward Network (FFN) for feature output, it tries to gather information within and across initial receptive fields.

$$F = MSA(\hat{F}) \tag{5}$$

Here $Concat()$ stands for the 3×3 convolutional layers; $Conv$ () signifies the concatenation operator. A multi-head self-attention system goes by the acronym MSA. According to the results, the study's head number is 4, which is also the stage number. In this case, "i" denotes the head's index., $i \in \{0, 1, 2, 3\}$.

5) POST-PROCESSING

The text areas we get can be made more expressive with the help of suitable post-processing algorithms applied to the obtained features. The research must execute binarization and label creation activities on the features before they can be parsed into the text areas.

a: DIFFERENTIABLE BINARIZATION

The binarization for the likelihood map was used by [45], which binarization technique to make probability map $\in R^{H\times W}$, where B∈R^(H×W) that is obligatory for a text or-not judging task. The following is a typical formulation of the conventional binarization process:

$$B_{i,j} = \begin{cases} 1 & \text{if } P_{i,j} \geq t \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

Pixel values (x, y) in the probability map are denoted by (i, j), and t is a predetermined threshold number. On the other hand, differentiable binarization shines when it comes to isolating closely jointed text instances and text regions from the background. Hence, the following is a proposed approximate step function:

$$\hat{B}_{i,j} = \frac{1}{1 + e^{-k(P_{i,j} - T_{i,j})}} \tag{7}$$

The above $\hat{B}$ is a learnt adaptive threshold map, and T is an approximate binary map. The hyperparameter k is empirically adjusted to 30 using the GSK optimisation model (discussed in Section IV-B6). This model mimics the behaviour of normal binarization but is differentiable, allowing it to be optimised during training alongside the proposed network. Here, the probability map for the binarization is used to determine the threshold for each pixel in the text border map.

b: LABEL GENERATION

It was PSENet that served as an inspiration for the probability map's label generation [46]. Typically, post-processing methods display results as a polygonal cluster of vertices.:

$$G = \{S_k\}_{k=1}^{n} \tag{8}$$

The labelling rule in different datasets typically determines the number of vertices, denoted as n, and the review findings in each data set are represented by the symbol S. In order to speech the challenge of defining the boundaries of nearby texts, the Vatti clipping technique was suggested as a means to efficiently produce an offset for reducing the size of the initial polygon. One can mathematically determine the offset D by using the formula:

$$D = \frac{Area(P) \times \left(1 - r^2\right)}{Perimeter(P)} \tag{9}$$

Located here the computation of the polygon area is denoted as Area (), the computation of the polygon perimeter is denoted as Perimeter (), and the shrink ratio, r, is analytically fixed to 0.4. The kernel for each text section is produced readily from the original ground truth using graphics-related processes, which are applied to the outcomes of reduced polygons.

The first step in obtaining the binary map is to binarize the probability map using a predetermined threshold, which is typically chosen as 0.2 in this case. Second, using the binary map, the research will group the text pixels into smaller sections. By applying an offset D' to the shrunken regions, the final text prediction results are enlarged.

$$D' = \frac{Area(P) \times r'}{Perimeter(P)} \tag{10}$$

6) HYPER-PARAMETER TUNING USING GSK

Every year, new optimisation methods are created and put into use to address practical issues. Thus, the gaining-sharing knowledge optimisation method (GSK) was suggested as a new optimisation algorithm not long ago [47]. GSK is an procedure that mimics the procedure of learning and sharing information throughout the course of a person's lifetime. Two crucial steps are junior gaining- knowledge, which are the fundamental mechanisms that GSK relies on.

- **Junior gaining and sharing knowledge:** At this point, the person is attempting to learn as much as they can from their immediate social network, which consists of friends, family, and neighbours, rather than from more extensive online resources like social media. Because they are still developing their capacity to classify individuals as good or bad, juniors share out of genuine interest and a want to learn from those around them, regardless of their level of expertise.
- **Senior gaining and sharing knowledge:** At this point in life, one has accumulated a wealth of life experience and has established relationships with a larger group of individuals, including friends, coworkers, and social networks. This is how they learn: by observing those closest to them. They also have a great knack for sorting people into categories like "best," "better," and "worst" at this stage. This leads them to hone their abilities and share what they've learned with the right people. There are multiple stages to the exact description of the aforementioned GSK procedure.:
- Booting of the essential factors, such as N—the populace size, which agrees to the sum of people. Loading of the starting populace is random while regarding the boundary restraints, where $x_i (i = 1, 2, 3, \ldots, N)$ characterize the persons; each x_i corresponds to x_{ih} with $x_{ih}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{id})$, deferring to the potential array of academic specialisations. Put another way, it's like a specialisation that someone is given. A review of the fitness level of the populace renowned as $f_j (j = 1, 2, 3, \ldots, N)$ is also conducted.
- The following nonlinear equation is used to determine the dimension separating junior and senior.:

$$d\,(junior) = Problemsize * \left(1 - \frac{G}{Gen}\right)^k \tag{11}$$

$$d\,(senior) = Problemsize - d(junior) \tag{12}$$

The junior phase's dimension is d(junior), and the senior phase's dimension is d(senior). k is the knowledge rate, which is greater than zero. The sum of generations is denoted by G, and the extreme sum of generations is represented by Gen.

- The time where juniors gain and share knowledge starts in this step. At this point, everyone is they can from their small network while also doing their best to pass on what they've learned. At this stage, their curiosity drives their interactions, thus it doesn't matter if the people they meet are from their network or not.

Algorithm 1 Phase 1: Junior Gaining And Sharing Facts [47].

for i = 1: (N) do
for h = 1: (d) do
  if $rand \leq k_r$(knowledge ratio) then
  if
$f(x_i) > f(x_{ran})(x_{ran} \textit{is a randomly selected individual})$ then
    $x_{ih}^{new} = x_h * K_f[(x_{(i-1)} - x_{(i+1)}) + (x_{ran} - x_i)]$
  else
    $x_{ih}^{new} = x_h * K_f[(x_{(i-1)} - x_{(i+1)}) + (x_i - x_{ran})]$
    end
  else
    $x_{ih}^{new} = x_{ih}^{old}$
end
end
end

- The present stage's persons are now updated in accordance with the junior plan.

– The participants are decided in climbing order according to the standards of the goal function. - In order to learn about each person, we pick the best and worst options that are closest to them. Furthermore, one is chosen at random to impart wisdom.

- This step procedure is exposed in Procedure 1. K_f is the facts factor, where $K_f > 0$; this limit controls the amount of information that is successful to individual. k_r is the knowledge ratio, where $k_r \in [0, 1]$; How much information can be transferred from one person to another is controlled by this limit.
- The senior knowledge phase is at this phase. A person's ability to be classified is taken into consideration at this level. At this point, the setup looks like this:

– First, the standards of the objective purpose sort the persons in dominant order.

– Then, those entities are divided into three collections: best, for example: $Best = 100p\%(x_{best})$, $Middle = N - (2 * 100p\%)(x_{middle})$, and $Worst = 100p\%(x_{worst})$.

– Now, two vectors are selected from gaining $(100p\%)$, while central is chosen for sharing $N - (2 * 100p\%)$. p here entities, where $p \in [0, 1]$. This phase procedure is exposed in Algorithm 2.

7) LOSS FUNCTION

For training the projected system, function can be expressed as:

$$L = L_s + a \times L_b + \beta \times L_t \tag{13}$$

The scheme assigns diverse weights to the likelihood map loss Ls, the loss L_b, and the threshold map Lt accordingly.

Algorithm 2 Phase 2: Senior Sharing Knowledge [47]

for i = 1: (N) do
 for h = 1: (d) do
  if $rand \leq k_r$ then
    if $f(x_i) > f(x_{ran})$ then
      $x_{ih}^{new} = x_h * K_f[(x_{best} - x_{worst}) + (x_{middle} - x_i)]$
    else
    $x_{ih}^{new} = x_h * K_f[(x_{best} - x_{worst}) + (x_i - x_{middle})]$
    end
    else
      $x_{ih}^{new} = x_{ih}^{old}$
    end
  end
end

In repetition, we set α as 1.0 and β as 10, correspondingly. For L_s and L_b, the function used here is [48] and [49]. Aiming to negatives, which happens in text finding approaches, hard negative removal is functional in the BCE hard negatives and expressed as shadows:

$$L_s = L_b = \sum\nolimits_{i \in S_l} y_i log x_i + (1 - y_i) log(1 - x_i) \tag{14}$$

where S_l is the set tested by a ratio at 1: 3, which is Mining (OHEM). To calculate L_t, the study uses L_1 distances to degree the resemblance among the forecast and label confidential the polygon:

$$L_t = \sum\nolimits_{i \in R_d} \left| y_i^* - x_i^* \right| \tag{15}$$

At this time, R_d is a pixel confidential the opened polygon; y^* is the tag for x∗ is the forecast likelihood map.

V. EXPERIMENTATION, RESULTS AND DISCUSSION

A. EXPERIMENTAL SETUP

The following features are present in the system that is utilised to implement this concept. The manufacturer and model of the computer are HP, and the operating system is Windows 10 Home. The system's CPU is an Intel(R) Pentium(R) CPU A1020 with 4 logical processors and 2.41 GHz of speed and 2408 MHz of memory.

B. EVALUATION METRICS

Real values that are known and can be found using a confusion matrix are used to make the number of predictions, which are then classified as correct or erroneous. Results for $TrueNegative(TN)$, $FalsePositive(FP)$, $and\ TrueNegative(TP)$ are displayed in the confusion matrix for data fitting based on classes of positive and negative. The model was assessed using a variety of criteria, including the F1 score, recall, accuracy, and precision. Accuracy: It evaluates the model's generalizability in terms of its ability to improve performance across different kinds of classes. Estimation is at its best when every choice is useful and significant. The formula is calculated by in-between the sum of precise judgements by the total sum of judgements.

$$Accuracy = ((TP + TN))/((TP + TN + FP + FN)) \quad (16)$$

Precision: It establishes the model's positive trial classification accuracy [33]. The sum of all positive cases divided by the sum of positive samples that were correctly or erroneously identified yields this value.

$$Precision = TP/(TP + FP) \quad (17)$$

Recall: The model's ability to classify positive samples is shown by this score. The volume of positive samples divided by the sum of positive trials that were precisely identified as positive is the formula for the percentage.

$$Recall = \frac{TP}{(TP + FN)} \quad (18)$$

F1-measure: A harmonic mean of accuracy is used to estimate the F1-measures.

$$F1 - measure = \frac{(2 \times precision \times recall)}{(Precision + recall)} \quad (19)$$

Figure 3 presents the accuracy and loss for data, where Figure 4 provides the ROC curve of the proposed model.

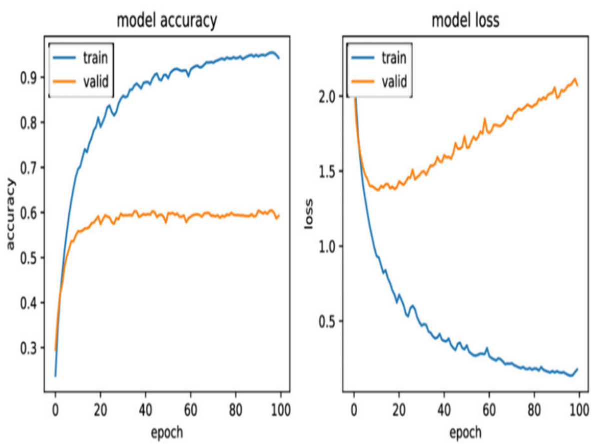

FIGURE 3. Accuracy and Loss of projected perfect.

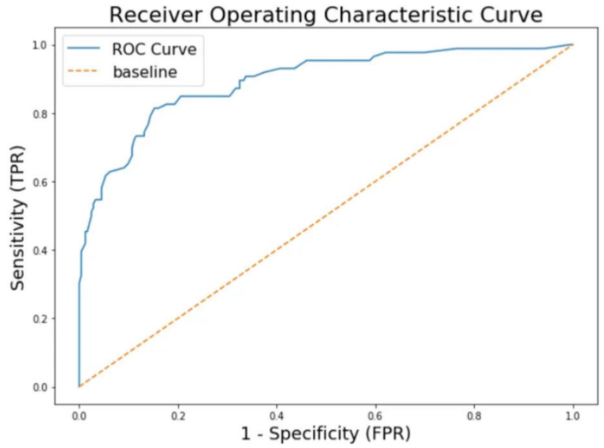

FIGURE 4. ROC Curve of the projected model.

TABLE 2. Accuracy evaluation.

Database Name	Accuracy (%)					
	MLP [23]	SVM [23]	DBN [23]	CNN [21]	LSTM	Proposed
cds_and_vinyl	85	84	86	80	84	95
books	84	82	85	81	85	94
electronics	82	81	84	82	86	96
office_products	83	83	84	84	86	95
cell_phones_and_accessories	81	84	86	84	84	94
musical_ instruments	82	82	86	82	84	96
patio_lawn_and_ garden	83	83	85	85	86	94
sports_and_ outdoors	84	81	86	84	85	95
grocery_and_ gourmet_food	82	82	86	82	85	94
arts_crafts_and_ sewing	81	84	85	86	84	93
clothing_shoes_ and_ jewelry	82	85	84	85	85	96

C. VALIDATION ANALYSIS OF PROPOSED MODEL

Table 2 to 5 presents the comparative investigation of various models in terms of different metrics for different review data.

Table 2 presents the Accuracy Evaluation. The projected model achieved an accuracy of 95, while the MLP [23] model realized 85, the SVM [23] model achieved 84, the DBN [23] model reached 86, the CNN [21] model accomplished 80, and the LSTM model achieved 84. Subsequently, the MLP [23] model accomplished 84, the SVM [23] model attained 82, the DBN [23] model reached 86, the CNN [21] model achieved 81, the LSTM model accomplished 85, and the proposed model achieved 94. Moving to the electronics database, the MLP [23] model realized an accuracy of 82, while the SVM [23] model achieved 81, the DBN [23] model reached 86, and the CNN [21] model achieved 82. In contrast, the projected model achieved an accuracy of 96. Afterwards, the MLP [23] model achieved an accuracy of 83, the SVM [23] model attained 83, the LSTM model reached 86, and the proposed model ultimately achieved an accuracy of 95.

Following that, the MLP [23] model achieved an accuracy of 81, the SVM [23] model attained 84, the DBN [23] model reached 86, the CNN [21] model achieved 86, and the LSTM model accomplished 84. Concurrently, the proposed model realized an accuracy of 94. Subsequently, the MLP [23] model achieved an accuracy of 82, the SVM [23] model attained 82, the DBN [23] model reached 86, the CNN [21] model succeeded in achieving an accuracy of 82, the LSTM model achieved 84, and the proposed model achieved 96.

Afterwards, the MLP [23] model attained an accuracy of 83, the SVM [23] model attained 83, the DBN [23] model reached 86, the CNN [21] model accomplished 85, and the LSTM model achieved 86. The projected model accomplished an accuracy of 94, corresponding to the projected model's accuracy. Next, the MLP [23] model found an accuracy of 84, the SVM [23] model found 81, the DBN [23] model found 86, and the CNN [21] model found 86. The proposed model, on the other hand, achieved an accuracy of 95. Following that, the MLP [23] model achieved an accuracy of 82, the SVM [23] model accomplished 82, the DBN [23] model reached 86, the CNN [21] model accomplished 86, the LSTM perfect managed to achieve an accuracy of 85, and the proposed model achieved 94. Afterwards, the MLP [23] model found an accuracy of 81, the SVM [23] model found 84, the DBN [23] model found 86, the CNN [21] model found 85, and the LSTM model found 86. The proposed model, in contrast, found an accuracy of 93. Following that, the MLP [23] model accomplished an accuracy of 82, the SVM [23] model attained 85, the DBN [23] model accomplished 86, the CNN [21] perfect achieved 84, and the LSTM perfect accomplished 85. Concurrently, the proposed perfect achieved an accuracy of 96.

TABLE 3. Validation analysis in terms of precision.

Database Name	Precision (%)					
	MLP [23]	SVM [23]	DBN [23]	CNN [21]	LSTM	Proposed
cds_and_vinyl	85	86	85	86	86	94
books	86	88	87	87	86	95
electronics	84	84	87	86	84	95
office_products	89	85	86	87	85	96
cell_phones_and_accessories	87	86	85	88	87	94
musical_ instruments	88	87	89	84	88	95
patio_lawn_and_ garden	86	82	87	85	85	93
sports_and_ outdoors	85	86	88	86	86	94
grocery_and_ gourmet_food	85	89	85	87	87	95
arts_crafts_and_ sewing	86	87	86	86	85	96
clothing_shoes_ and_jewelry	87	86	87	85	82	95

The Validation Analysis, characterized in terms of precision in Table 3, is noteworthy. In the analysis of the cds_and_vinyl database, the MLP [23] model achieved a precision of 85, the SVM [23] model attained 86, the DBN [23] model reached 85, the CNN [21] model achieved 86, and the LSTM model accomplished 86. The proposed model achieved 94, corresponding to the precision of the proposed model.

Additionally, in the books database, the MLP [23] model attained a precision of 86, the DBN [23] LSTM model achieved 87, and the proposed model accomplished a precision of 95. Moving to the electronics database, the MLP [23] model achieved a precision of 84, the SVM [23] reached 84, the DBN [23] attained 87, the CNN [21] achieved 86, the LSTM reached 84, and the Proposed model attained a precision of 95. In the cell_phones_and_accessories database, the MLP [23] model reached a precision of 87, the SVM [23] achieved 86, the DBN [23] attained 85, the CNN [21] achieved 88, the LSTM reached 87, and the Proposed model attained a precision of 94. Following that, in the sports_and_outdoors database, the MLP [23] model achieved a precision of 85, the DBN [23] model attained 86, the LSTM model achieved 88, and the proposed model reached 94. For the patio_lawn_and_garden database, the MLP [23] model achieved a precision of 86, the SVM [23] reached 82, the DBN [23] attained 87, the CNN [21] achieved 85, the LSTM reached 85, and the proposed model reached 93. For the grocery and gourmet food database, the MLP [23] model achieved a precision of 85, the DBN [23] model attained 89, and the CNN [21] model achieved 85. Additionally, the LSTM achieved 87, and the Proposed model reached a precision of 95. In the arts_crafts_and_sewing database, the MLP [23] model achieved a precision of 86, the SVM [23] reached 87, the DBN [23] attained 86, the CNN [21] achieved 86, the LSTM reached 85, and the proposed model reached 96. Finally, in the clothing, shoes, and jewelry database, the MLP [23] model achieved a precision of 87, the SVM [23] reached 86, the DBN [23] attained 87, the CNN [21] achieved 85, the LSTM reached 82, and the proposed model achieved 95. Furthermore, the proposed model attained a precision of 95.

Table 4 presents a comparative analysis of various models in terms of recall. In the analysis of the cds_and_vinyl database, the MLP [23] model achieved a recall of 85, SVM [23] reached 88, DBN [23] reached 84, CNN [21] reached 85, and LSTM reached 85. The proposed model achieved a recall of 94 accordingly. Moving to the books database, the MLP [23] model, SVM [23], DBN [23], and CNN [21] all reached recall values of 85, 82, and 94, respectively. LSTM also reached recall values of 85, and CNN [21] achieved 94.

TABLE 4. Comparison analysis of different models in terms of recall.

Database Name	Recall (%)					
	MLP [23]	SVM [23]	DBN [23]	CNN [21]	LSTM	Proposed
cds_and_vinyl	88	85	86	84	85	95
books	85	82	85	82	85	94
electronics	84	84	84	83	87	96
office_products	86	83	86	84	86	92
cell_phones_and_accessories	84	82	82	85	84	94
musical_ instruments	85	84	88	84	85	95
patio_lawn_and_ garden	84	85	86	81	86	96
sports_and_ outdoors	86	86	87	82	85	94
grocery_and_ gourmet_food	85	84	87	83	84	91
arts_crafts_and_ sewing	82	85	84	84	86	94
clothing_shoes_ and_ jewelry	83	86	85	85	87	95

In the electronics database, the MLP [23] model, SVM [23], DBN [23], CNN [21], LSTM, and the proposed model achieved recall values of 96, 84, 85, 86, and 86, respectively.

Using the office_products database, the proposed model achieved a recall of 92, while the MLP [23] model reached 86, SVM [23] reached 83, CNN [21] reached 84, and LSTM reached 86. For the cell_phones_and_accessories database, the MLP [23] model, LSTM, DBN [23], CNN [21], LSTM, and the proposed model all achieved recall values of 94, 85, and 82, respectively. In the musical_instruments database, the MLP [23] model achieved a recall of 85, SVM [23] reached 84, DBN [23] reached 88, CNN [21] reached 84, LSTM reached 85, and the proposed model attained a recall of 95. Similarly, for the patio_lawn_and_garden database, the MLP [23] model reached a recall of 84, SVM [23] reached 85, DBN [23] reached 86, CNN [21] reached 81, LSTM reached 86, and the proposed model attained a recall of 96. Next, in the grocery_and_gourmet_food database, the MLP [23] model reached recall as 85, SVM [23] reached 84, CNN [21] reached 87, CNN [21] reached 84, CNN [21] reached 86, DBN [23] reached 87, CNN [21] reached 82, and LSTM reached 85. The proposed model attained a recall of 94 accordingly. Using the arts_crafts_and_sewing database, the proposed model achieved a recall of 94, while the MLP [23] model reached a recall of 82, DBN [23] reached a recall of 85, and CNN [21] reached a recall of 84. Finally, in the clothing, shoes, and jewelry database, the proposed model achieved a recall of 95, while the MLP [23] model reached a recall of 83, DBN [23] reached a recall of 86, CNN [21] reached a recall of 85, and LSTM reached a recall of 87.

Table 5 illustrates the Verification of the projected model based on F1-measure. In the analysis of the cds_and_vinyl database, the MLP [23] model achieved an F1-measure of 86, DBN [23] reached 87, CNN [21] reached 85, LSTM reached 87, and the Proposed model attained an F1-measure of 94. Moving to the books database, the MLP [23] model achieved an F1-measure of 85, DBN [23] reached 82, LSTM reached 84, and the Proposed model attained an F1-measure of 95. In the electronics database, the MLP [23] model reached an F1-measure of 84, SVM [23] reached 84, DBN [23] reached 84, CNN [21] reached 84, LSTM reached 85, and the Proposed model attained an F1-measure of 94. Using the office_products database, the MLP [23] model achieved an F1-measure of 86, DBN [23] reached 86, CNN [21] reached 85, LSTM reached 86, and the Proposed model attained an F1-measure of 93. For the cell_phones_and_accessories database, the MLP [23] model reached an F1-measure of 87, DBN [23] reached 85, CNN [21] reached 89, LSTM reached 88, and the Proposed model attained an F1-measure of 96. In the musical_instruments database, the MLP [23] model achieved an F1-measure of 89, DBN [23] reached 87, CNN [21] reached 83, LSTM reached 87, and the Proposed model attained an F1-measure of 95. Similarly, in the patio_lawn_and_garden database, the MLP [23] model reached an F1-measure of 85, DBN [23] reached 86, CNN [21] reached 85, LSTM reached 86, and the Proposed model attained an F1-measure of 93. For the sports_and_outdoors database, the MLP [23] model reached an F1-measure of 84, DBN [23] reached 85, CNN [21] reached 86, LSTM reached 85, and the Proposed model attained an F1-measure of 94. In the grocery_and_gourmet_food database, the MLP [23] model reached an F1-measure of 87, CNN [21] reached 84, LSTM reached 89, and the Proposed model attained an F1-measure of 92. Using the arts_crafts_and_sewing database, the MLP [23] model reached an F1-measure of 88, DBN [23] reached 87, CNN [21] reached 85, LSTM reached 84, and the Proposed model attained an F1-measure of 91. In the clothing_shoes_and_jewelry database, the MLP [23] model reached an F1-measure of 86, DBN [23] reached 85, CNN [21] reached 85, LSTM reached 85, and the Proposed model attained an F1-measure of 94.

TABLE 5. Verification of proposed model on f1-measure.

Database Name	F1-Measure MLP [23]	SVM [23]	DBN [23]	CNN [21]	LSTM	Proposed
cds_and_vinyl	86	86	87	85	87	94
books	85	85	82	84	86	95
electronics	84	84	84	84	85	94
office_products	86	86	86	85	86	93
cell_phones_and_accessories	87	85	89	86	88	96
musical_ instruments	89	87	87	83	87	95
patio_lawn_and_ garden	85	86	85	86	85	93
sports_and_ outdoors	84	85	86	85	84	94
grocery_and_ gourmet_food	87	84	84	84	89	92
arts_crafts_and_ sewing	88	87	86	85	84	91
clothing_shoes_ and_jewelry	86	86	85	84	85	94

VI. CONCLUSION AND FUTURE WORK

Our aim in composing this article was to contribute to the field of sentiment analysis by elucidating the methods, tools, and datasets employed to train our model for accurately predicting customer reviews on Amazon. The primary focus of this investigation was on product and customer review sentiment analysis across social media and product websites. To tackle the limited receptive fields and inadequate modeling capabilities of the initial CNN module for review categorization, this study proposes a DPTN, or double-path transformer network. The suggested bidirectional interactions between two parallel branches in DPTN augment both local and global perspectives. Additionally, by adjusting the hyper-parameters using the GSK optimization method, the proposed DPTN model enhances the classification performance metrics used to evaluate the efficacy of these models on the aforementioned datasets. A comparison of the final results with those of previously established methods was conducted, and the suggested outcomes proved to be satisfactory, either comparable to or even surpassing prior methods.

Some potential limitations of the research paper include:

- The study focuses specifically on customer reviews on Amazon, which may limit the generalizability of the findings to other platforms or domains. The effectiveness of the proposed DPTN model may vary when applied to datasets from different sources or industries.
- Although the GSK optimization method is utilized to adjust hyperparameters and enhance model performance, the sensitivity of the proposed DPTN model to hyperparameter settings might present challenges in practical deployment or fine-tuning.

Looking ahead, there is scope for further exploration in enhancing sentiment analysis techniques. Future studies can delve into integrating self-attention representations with diverse word embedding techniques within deep learning frameworks to better understand user interests and provide recommendations. Addressing these areas will build upon our work and contribute to advancing sentiment analysis methodologies.

AUTHOR CONTRIBUTIONS

All authors contributed equally.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available upon reasonable request from the authors.

ETHICS APPROVAL

The submitted work is original and has not been published elsewhere in any form or language.

DISCLOSURE OF POTENTIAL CONFLICTS OF INTEREST

There is no potential conflict of interest.

RESEARCH INVOLVING HUMAN PARTICIPANTS AND/OR ANIMALS

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LELLA KRANTHI KUMAR is currently an Assistant Professor with the School of Computer Science and Engineering, VIT-AP University, Amaravati, Andhra Pradesh, India. He possesses a strong passion for acquiring new knowledge and applying it to address real-world challenges. Driven by a keen interest in global technological advancements, he keeps a close eye on all the latest developments in the tech world. While he may not fit the stereotype of a nerd, he is socially conscious and attuned to everything happening around him. This research effectively leverages the current network infrastructure, making the learning process accessible to people of diverse backgrounds around the world. His research interests include data analytics, speech processing, audio AI, the IoT, and medical image processing.

VENKATA NAGARAJU THATHA received the Ph.D. degree in machine learning from JNTUK. He is currently an Associate Professor with the Department of Information Technology, MLR Institute of Technology, Hyderabad, Telangana, India. He is a young and dynamic individual with a strong academic background in computer science and engineering. His research interests include machine earning, natural language processing, and blockchain technology. He has more than 12 years of experience in the research and academics. His research findings have been published in SCIE and Scopus indexed international journals. He has attended and presented many research papers in IEEE and springer international conferences. He also published 12 patents.

PAMULA UDAYARAJU received the bachelor's degree in computer science and engineering from Velagapudi Siddhartha Engineering College, Vijayawada, Affiliated to Acharya Nagarjuna University, Guntur, in 2010, and the M.Tech. degree in CST from the Sagi Ramakrishnam Raju Engineering College, Bhimavaram, Affiliated to JNTU Kakinada, in 2014. He is currently pursuing the Ph.D. degree in the field of image processing and deep learning with Sathyabama University, Chennai. He is also an Assistant Professor with the Department of Computer Science and Engineering, Sagi Rama Krishnam Raju Engineering College, Andhra Pradesh, India. His research interests include genome sequencing, image processing, machine learning, deep learning, 5G networks, and the IoT applications.

D. SIRI received the B.Tech. degree in information technology and the M.Tech. degree in computer science and engineering from JNTUH, Hyderabad, and the Ph.D. degree from JJT University Rajasthan. She is currently an Assistant Professor with the Department of CSE, Gokaraju Rangaraju Institute of Engineering and Technology, Bachupally, Telangana, India. She has published two articles in international journals and one paper in national and international conferences. Her research interests include machine learning, software engineering, and the IoT.

G. UDAY KIRAN received the M.Tech. degree in neural networks from Jawaharlal Nehru Technological University Kakinada and the Ph.D. degree in data mining from Jawaharlal Nehru Technological University Hyderabad. Currently, he is an Associate Professor with the Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning), B. V. Raju Institute of Technology. He has 15 years of teaching experience. His research interests include deep learning, natural language processing, computer vision, algorithms, and analysis.

B. N. JAGADESH (Senior Member, IEEE) is currently an Associate Professor with the School of Computer Science and Engineering, VIT-AP University, Amaravathi, India. He has published more than 30 research articles in national and international journals with high reputation. His research interests include image processing, medical image analysis, multi-modal biometrics, and speech recognition.

RAMESH VATAMBETI received the B.Tech. degree in computer science and engineering from Sri Venkateswara University, Tirupati, and the M.Tech. degree in IT and the Ph.D. degree in CSE from Sathyabama University, Chennai. He has around 18 years of teaching experience from reputed Engineering Institutions. He is currently a Professor with the School of Computer Science and Engineering, VIT-AP University, Amaravati, India. He has successfully guided three Ph.D. scholars. His research interests include computer networks, mobile ad-hoc and sensor networks, and machine learning.