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Enhancing Graph-Based Sentiment Analysis Models with Hill Climbing

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ABSTRACT

In the current study, sentiment graphs were constructed in which the nodes represented emotion-laden words, and the edges depicted their weighted semantic associations. To improve the model, the hill climbing method was employed, which iteratively adjusted parameters to achieve increasingly higher classification accuracy. The developed system employed a combination of graph neural networks (GNNs) and hill climb- based optimisation to improve the efficiency of sentiment categorisation. The experiment's outcomes reveal that the suggested model reached a maximum accuracy of 96.95%, which is higher than traditional sentiment analysis methods and thus proves its appropriateness for emotion-aware text representation. The experimental findings confirm that GNN-based sentiment representation and hill climbing optimisation effectively leverage the intricate emotional relationships, resulting in better sentiment classification. The graphs illustrating optimisation progress and the structure of the sentiment graph further demonstrate the effectiveness of our method.

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1. INTRODUCTION TO SENTIMENT ANALYSIS AND GRAPH NEURAL NETWORKS

A. The Landscape of Sentiment Analysis

Sentiment analysis refers to the identification and classification of the emotions expressed in a text that can be achieved using sentiment analysis [17].This involves finding out whether the information carries a neutral, negative, or positive attitude. Sentiment analysis plays a critical role in comprehending the opinions of the population and deriving subjective data from Internet materials [5]. The growth of social media and the Internet has led to the vast amount of text data generated by users, and sentiment analysis has become a significant issue for various applications. Conventional approaches may struggle with linguistic intricacies and fail to consider more intricate contextual connections among words. Such methods usually rely on machine learning algorithms trained on large datasets, such as unigrams, n-grams, and Part-Of-Speech tags. The automatic identification of feelings conveyed in textual input is beneficial for multiple applications. These are personalized recommendations, user modeling, crisis management, and business intelligence. Similarly, e-commerce companies can employ sentiment analysis to monitor their brand reputation by tracking both online reviews and social media mentions. Political campaign-related news articles and social media posts can be analyzed to gauge public opinion regarding candidates and issues.Crisis management teams can also identify and respond to emerging crises by monitoring social media discussions about their organization. Enhanced personalized recommendations can be achieved by incorporating user sentiment data for a range of products and services. Traditional methods of sentiment analysis frequently overlook the relationship between words and the surrounding context that can be utilised to accurately capture the sentiment [17]. The reason is that these methods typically accomplish this by treating words as individual units, disregarding their semantic connections. Words such as 'not good' would serve to convey both negative and positive meanings, which is obviously incorrect. Graph Neural Net-

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works (GNNs) offer an alternative approach, capable of forming connections between words in a sentence to mimic understanding and replicate the sentence's original meaning [17]. GNNs can also be used to encode the dependencies and contextual information that are important for correctly classifying sentiment. This is done by making sentiment graphs where words or ideas are shown as the vertices, and the edges show the semantic connections between two nodes.

B. GNN for Sentiment Analysis

GNNs can also be used to encode the dependencies and contextual information that are important for correctly classifying sentiment. This is done by making sentiment graphs where words or ideas are shown as the vertices, and the edges show the semantic connections between two nodes. [10] Such relations may be synonyms, antonyms, etc. The semantic contextual connections of words through GNNs are used to clearly demonstrate how the text in the graph can hold significant information and dependencies, which contribute to the effective formation of the sentiment classifier [11]. Inside this Model, it can effectively capture dependencies and contextual information for sentiment classification by leveraging GNNs. There are many applications that clearly demonstrate how GNNs classify graphs and nodes [13].Node classification determines how individual nodes within a graph will be categorized, while graph categorization identifies the overall category or label of the entire graph. For example, GNNs have been used to classify social network users based on their connections and activities, and to classify molecules based on their structure and properties. GNNs are a novel deep learning architecture that models relationships within graph-structured data [18]. By utilizing the capabilities of graph representation alongside neural networks, GNNs have demonstrated potential across various tasks, including node classification, link prediction, and graph classification. GNNs have several uses that show promise, like capturing emotional dependencies, which make sentiment classification more accurate. They also found that brain imaging data can be useful in many areas, where they have shown that they can predict things like disease and sex. It is also very advantageous for predicting the weather, which is a big step forward in how we look at weather data and model atmospheric conditions. In the last few months, people have been genuinely interested in studying GNNs.

C. Hill Climbing Optimization

Hill Climbing is an optimization technique used to fine-tune model parameters and enhance the ability to capture emotional dependencies. This algorithm iteratively refines parameters to maximize classification accuracy. The optimization process involves making minor changes to the model parameters and evaluating the assessment of the model after each change. If a change enhances the model's evaluation, it will be accepted; if not, it will be discarded.

Hill climbing is a straightforward optimization technique used to find the best solutions to a problem by progressively adjusting the current solutions. This technique is beneficial, instrumental, handy,advantageous when the search space is too ample to explore exhaustively. The process begins by identifying the outcomes and gradually transitions to a neighboring outcome that improves the objective function. This algorithm stops as soon as it approaches a local optimum set, indicating that a single move would yield better results [10].

The merging of hill climbing with GNNs optimizes the model's parameters to improve classification accuracy, illustrating the prospects of using optimization algorithms with neural networks. This optimization activity enables the model to improve its parameters and adjust to the dataset's specific properties, leading to better performance through continuously fine-tuning model parameters. Hill Climbing assists the GNN in recognizing the challenging relationship between text and contextual information required for effective sentiment classification. The technique applied in this research study relies on NLP [4].

2. MOTIVATION FOR USING GRAPH-BASED SENTIMENT ANALYSIS WITH HILL CLIMBING

A. Limitations of Traditional Sentiment Analysis

Machine learning algorithms trained on large datasets are usually the backbone of traditional sentiment analysis methods, but they are not always capable of understanding the subtleties of human language. These algorithms usually use different features, such as unigrams, n-grams, and part-of- speech tags, to find sensitivity [19]. However, these methods frequently overlook the subtle intertextual links and contextual information necessary for accurate sentiment detection.

The dominance of word occurrences and shallow syntactic patterns in traditional methods results in a failure to recognize deeper semantic relationships [21]. The algorithm used in standard sentiment analysis identifies the word "happy" as positive; however, it struggles to determine the sentiment of the phrase "not happy." Unlike the traditional method, our method transcends word frequency and superficial syntactic patterns to venture into deeper semantic connections between words. Additionally, sentiment analysis is applied to understand and bring to life significant linguistic representations of human emotions.

B. Advantages of Graph-Based Approaches

GNNs have improved their ability to understand small differences in texts when they are presented in a way that avoids the problems with traditional methods. Using the text representation of a graph, GNNs can capture the relationships between words while also considering the necessary context for accurate sentiment detection. It is like giving the models a thorough understanding of what the context means and letting them figure out what the person meant. The graph-based models can illustrate various relationships between objects, reflecting real-world connections that are often challenging to identify through other means. Graphs are powerful tools that can depict intricate relationships between objects, leading to their widespread use in a variety of real-world scenarios.

The capabilities of neural networks are greatly dependent on their structure, which can considerably impair their ability. This dependence allows for the selection of specific generalization features one desires but ultimately results in reduced computational efficiency [17]. The journey of machine learning, which includes neural networks and traditional algorithms, has significantly impacted various fields, enabling the development of data-driven solutions and automation.

C. Rationale for Incorporating Hill Climbing

It helps adjust model parameters to maximize the acquisition of knowledge from emotional dependencies. This makes it possible to respond more quickly and effectively to changes in situations when they happen at random crossings of the search space. It finds its main application in sentiment analysis where the interplay of words and even the subtleties of language can be very complicated. It iteratively refines parameters to maximize classification accuracy and improve sentiment representation.

The optimization process allows the model to modify its parameters to align more effectively with the distinctive characteristics of the data set. This is important because different datasets can have different characteristics, like how they show sentiment or what kinds of language they use [21]. The model uses the unique features of the dataset to get better performance. Hill climbing helps GNN parameters fit better with the sentiment graphs so that they can better show emotional dependencies and context.

3. LITERATURE REVIEW AND BACKGROUND

Sentiment analysis is a key aspect of natural language processing (NLP) as it assesses a text based on the opinions, attitudes, and emotions of an individual or collective [20]. The application of sentiment analysis is beneficial across multiple domains, including business and social sciences [16]. People are interested in GNNs, a new type of deep learning architecture, because they can show how data that is structured like a graph is connected and dependent on other data [4]. By combining graph representation and neural networks, GNNs have shown that they can do many things well, such as node classification, link prediction, and graph classification [23]. Hill climbing is a simple way to improve a solution by making small changes to it over and over again until it gets better.The model can better understand the emotion being shown by using GNNs to find complicated links and dependencies between words in a phrase. Metrics like precision, recall, and accuracy show that this method improves feature extraction and uses KNN for classification [8].

The application of GNNs in sentiment analysis represents a nascent and rapidly evolving area of research [3]. Hill Climbing changes the model parameters to increase the ability to learn emotional dependencies. It is especially helpful for sentiment analysis, where the connections between words and the subtleties of language can be challenging to understand. It keeps changing parameters to improve the accuracy of classification and the representation of sentiment.

The goal of optimization is to change the rules in a machine learning algorithm so that it can learn about unique features in a dataset. This is important because different datasets can have different characteristics, such as different types of language or different sentiment distributions.

This study utilizes natural language processing in the implementation of the methodology. The technique can become more effective when used [15]. By correctly figuring out the connections and interdependencies between words, GNNs can make the model more open to the context and unique ways that people express their feelings [3]. The structure of a neural network has a big effect on how well it works, like how quickly it can process information and how well it can generalize [8]. Machine learning, which includes both classical algorithms and neural networks, has arrived at its goal. Machine learning has changed almost everything, enabling people to use data to solve their problems and automate their jobs. Neural language models like BERT and GPT have come onto the scene and have helped us a lot by giving us powerful text representations that make it easier to sort through emotions. Sentiment analysis is used to understand and respond to how people feel when they write [22].

4. METHODOLOGY

To improve sentiment analysis, the technique depicted in Figure 1 combines GNNs with Hill Climbing optimization. This part goes into excellent detail about how to prepare the dataset, make sentiment graphs, design and train the GNN model, and use the hill climbing optimization method. Following each stage is essential to learning the correct sentiment classification and comprehending the intricate workings of emotional relationships. Figure 2 clearly shows how to classify a sentiment dataset into three

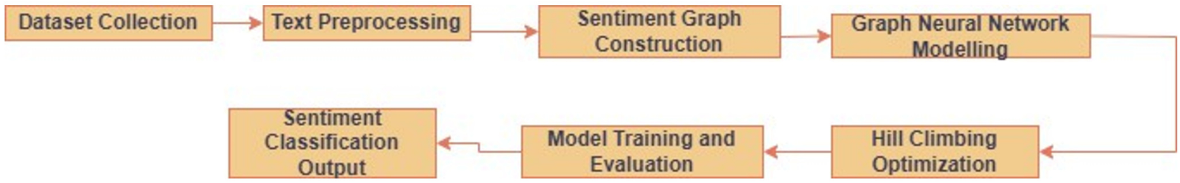

Fig.1: *Workflow of Proposed Sentiment Analysis Model.*

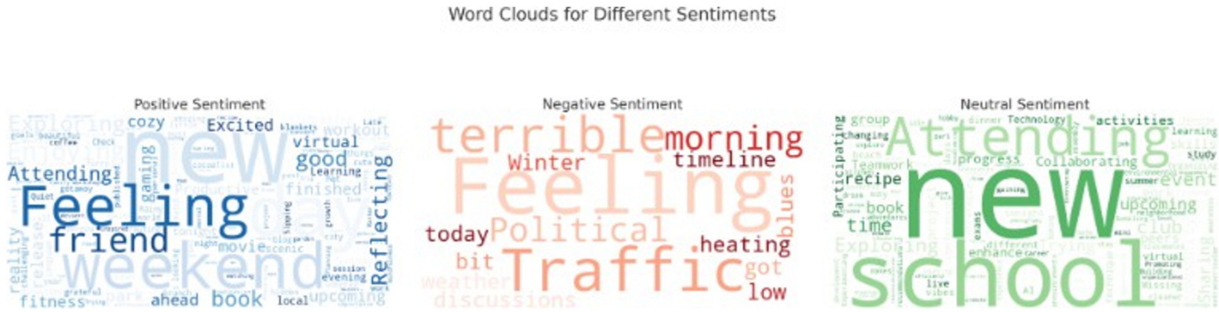

Fig.2: *World Cloud Dataset with Positive ,Negative and Neutral.*

groups: positive, negative, and neutral.

A. Dataset Description

This research employs a dataset comprising 10,000 texts sourced from various social media posts and product reviews on the Internet, including Amazon and mobile product evaluations, in Hindi and Hinglish [20]. The data set has three emotional categories: neutral (3,300 samples), negative (3,200 samples), and positive (3,500 samples). To improve the data, we removed unnecessary emojis, special characters, and other symbols from the texts. Thereafter, the texts were turned into tokens and made lowercase to make the data the same. This preprocessing step helps the Graph Neural Network (GNN) learn about trends and emotions in context while it is training.

Table 1: *Dataset Statistics.*

Attribute	**Value**
Total Samples	10,000
Positive Samples	3,500
Negative Samples	3,200
Neutral Samples	3,300
Language	Hindi, Hinglish

B. Sentiment Graph Construction

Creating the sentiment graph is an important step in sentiment analysis using a graphical neural network. The sentiment graphs that we have created had emotion words as nodes and semantic relationships with weights as edges [20]. This graph-based model assists in understanding the relationships between words and the emotions they evoke in individuals. In an emotion graph, nodes represent words or ideas, while edges illustrate the connections between these nodes' meanings [1]. GNNs can accurately classify sentiment by creating sentiment networks where nodes are words with concepts and edges are semantic connections. This gives them the background and connections they need to correctly sort feelings [6]. This is more than what traditional methods do in handling words as independent entities, which better captures human emotions.

C. Graph Neural Network (GNN) Modeling

3 and 4 show GNN trained to represent sentiment graphs. Inputs: Sentiments graphs built based on the text.

Input: Graphs of sensations based on the text.

Message Passing: The model can show semantic dependencies since nodes get data from their neighbors.

Creating Embeddings: Each node learns a low-dimensional vector representation that preserves its meaning and shape.

Graph-level Prediction: We combined the embeddings and applied a classifier to guess how the text made people feel in general.

D. Hill Climbing Optimization

To enhance the performance of the GNN model, Hill Climbing optimization was applied:

Initialization: Start with an initial set of model parameters.

Iteration: Slightly modify the parameters at each step.

Evaluation: Accept changes that lead to improved sentiment classification accuracy.

Convergence: Repeat until no further improvements are observed.

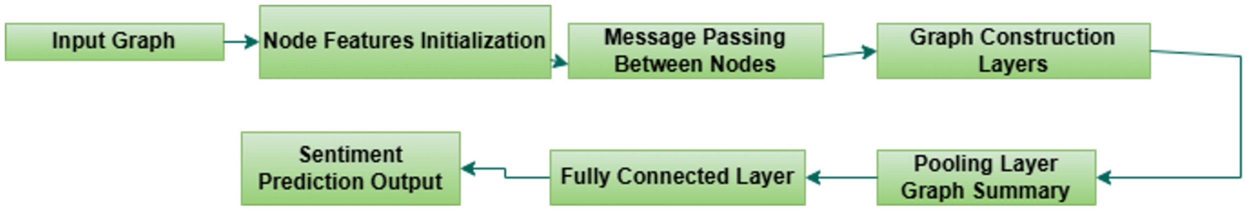

Fig.3: *Sentiment Graph Construction Model.*

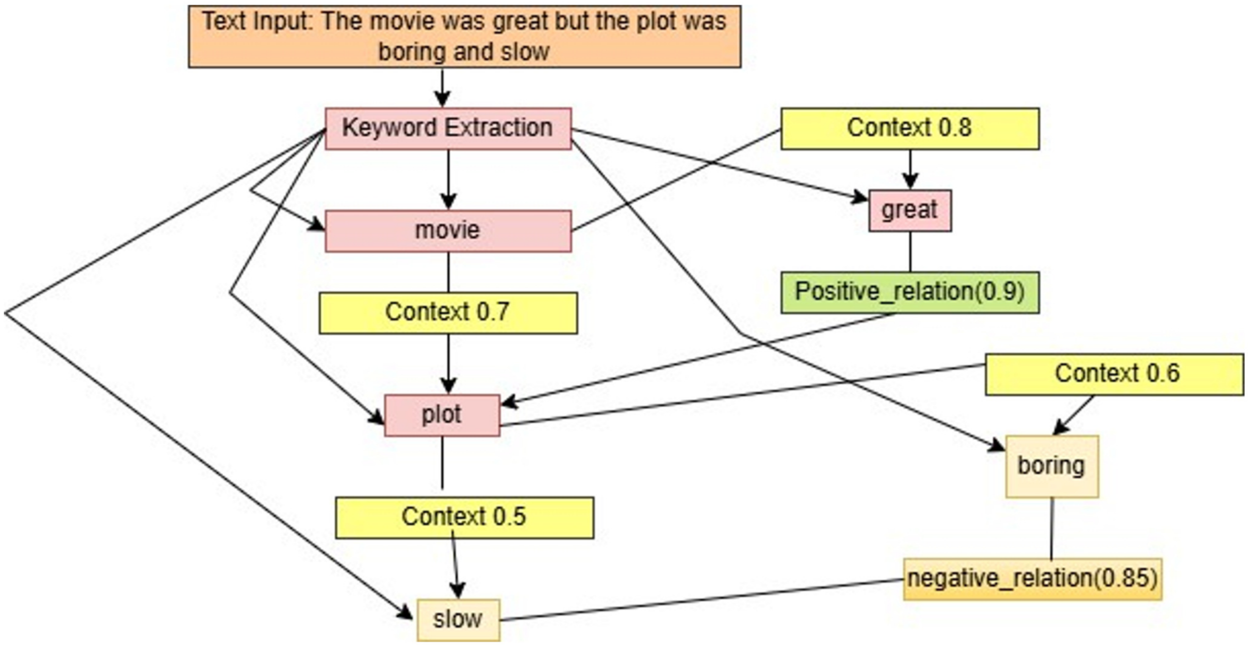

Fig.4: *Graphical Construction Layers.*

Hill Climbing helps change the GNN settings so that the sentiment graphs can better depict how emotions depend on each other and the situation.

The hill climbing optimisation method has a number of explicit steps that must be followed in order to work. The technique begins with an initial set of model parameters [3]. These parameters are the first step in the optimisation process. The algorithm then makes small changes to the parameters at each step. [7]. In most cases, these modifications are small, so the model doesn't change much from where it is presently.

The hill-climbing algorithm's main feature is that it can figure out how changing a parameter will change the result. There are updates to the algorithm that could improve sentiment classification. This technique makes sure that the model is always moving towards a better arrangement. The optimisation process is repeated until there are no more gains. The benefit of this convergence criterion is that it guarantees that the algorithm will stop when it finds a local optimum. Thereby, the system can change itself in a way that fits the data set much better. If the model learns how to work with the specific data set, it will work better. The indirect object functioning as an agent signifies challenges in authentic sentiment analysis [22].

Hill Climbing is highly crucial for changing the GNN settings so that the sentiment graphs may demonstrate how emotions are related to each other and the context [2]. By changing the GNN parameters, Hill Climbing helps the model learn more about the emotional meanings of words and how they relate to each other. This leads to better sentiment categorization in 5.

5. RESULTS & DISCUSSIONS

A. Databases

The findings of this study assess the efficacy of the proposed methodology, which integrates GNNs with hillclimb optimisation for sentiment analysis. This strategy is more accurate than traditional ones, showing that this integrated approach works better.

B. Hill Climbing Optimization Performance

The hill-climbing algorithm was used to determine the best settings for the model that looks at sentiment. Figure 6 shows that the accuracy stayed fairly stable at around 96.95% for each iteration. The model converged quickly, and the accuracy didn't im-

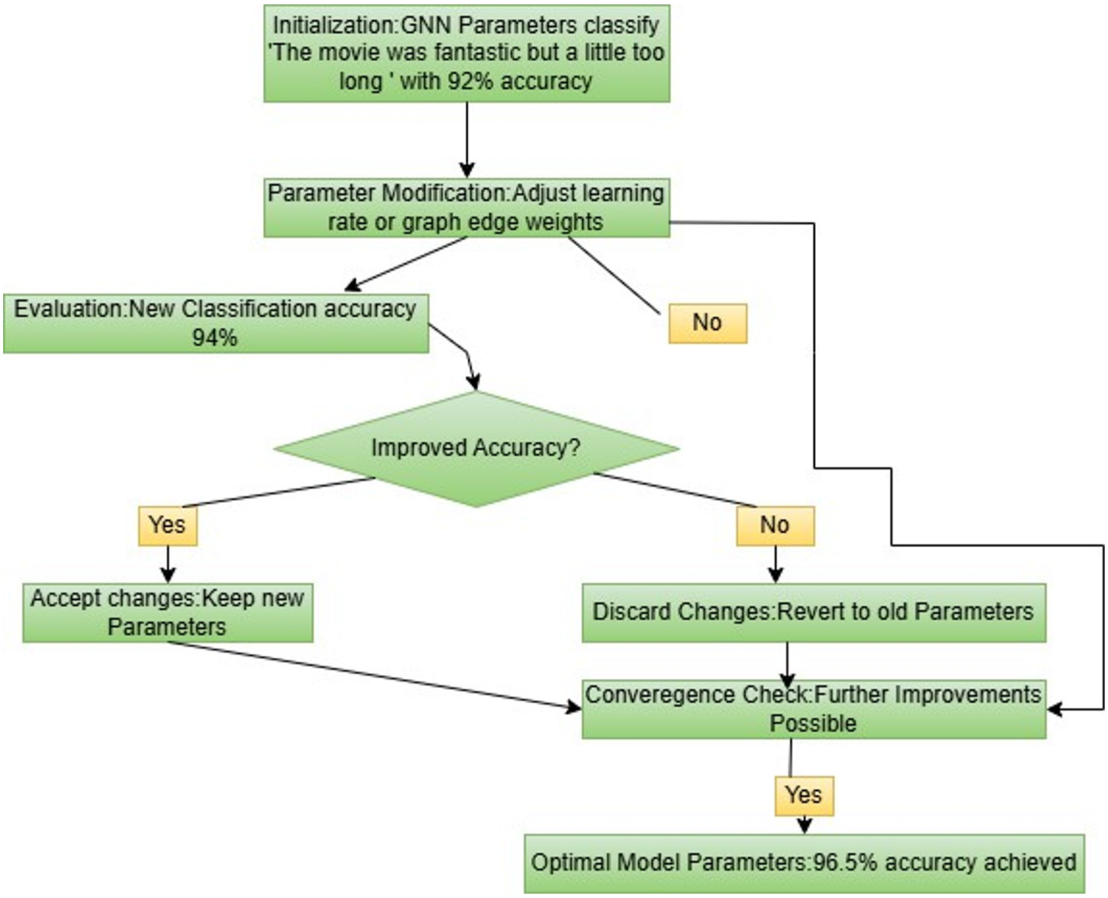

Fig.5: *Sentiment Prediction Output.*

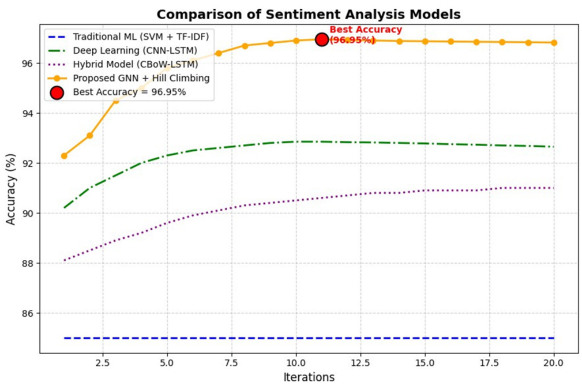

Fig.6: *Hill Climbing optimization performance with a display of accuracy improvement over time. The model converges quickly, maintaining a consistent accuracy of approximately 96.95%.*

prove much after the first change in parameters, as shown by the highest accuracy of 0.9695.

This plateau indicates that the model might have attained a local optimum early in the search space. One likely reason is that the starting weights and heuristics were already close to the best they could be, or the search space wasn't big enough to make a big difference. This situation shows that hill climbing can quickly improve models, but they might not be able to get out of local maxima.

C. Graph-Based Sentiment Representation

Figure 7 shows how sentiment words are related to each other based on how similar they are or how often they arise together. The edge weights tell you how similar the meanings are. "Happy," "joyful", and "great" are all words that go together to provide a powerful positive sentiment combination. A set of words that express a negative feeling includes "sad", "angry", and "bad".

This graph-based model validates the semantic clustering expected in sentiment analysis tasks. The high edge weights (like 0.88 between happy and joyful) show that the word embedding or similarity metric used is trustworthy. This type of graph can assist models be more clear and open, giving an AI view on how to sort feelings.

D. Insights and Limitations

The optimization achieved a consistent high level of accuracy; however, the lack of substantial progress indicates that future efforts should explore more robust metaheuristic techniques, such as genetic algorithms or simulated annealing. Moreover, the graph

Table 2: *Comparative Analysis of Sentiment Analysis Models.*

Model	Technique Used	Accuracy (%)	Remarks
Traditional ML (SVM with TF-IDF)	Manual feature extraction	87.30	Lacks deep semantic context
CNN-LSTM	Deep learning (seq-based)	92.85	Captures sequence info but misses word relationships
(CBoW-LSTM)CBoW-LSTM	CBoW-LSTM	88.30	Basic word embedding with sequence modeling; limited relational context [15]
(CBoW-LSTM)CBoW-CNN-LSTM	CBoW-CNN-LSTM	88.50	Better feature extraction and sequence capture [19]
(CBoW-LSTM)TF-IDF-CNN-LSTM	TF-IDF-CNN-LSTM	88.50	Uses statistical and deep features; improved generalization [19]
CNN-LSTM	Deep learning (seq-based)	92.85	Captures sequence info but misses word relationships
Proposed Model	**GNN + Hill Climbing**	**96.95**	Balanced accuracy with explainability and efficiency

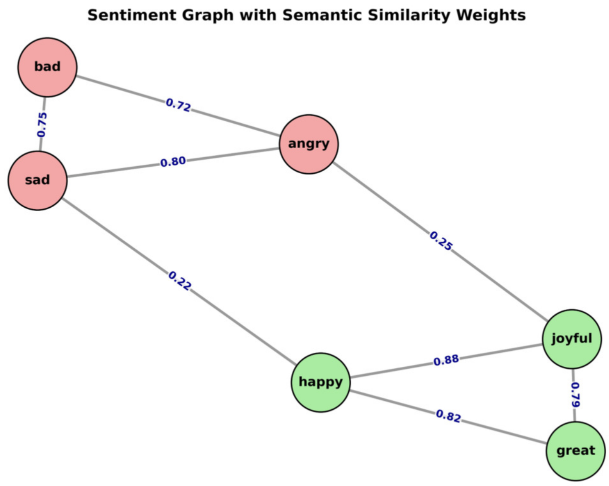

Fig. 7: *Sentiment graph visualization of the semantic relationships between emotion-filled words. Clusters of positive and negative sentiments (e.g., "happy–joyful" and "sad–angry") are clearly differentiated by edge weights.*

model, though interpretable, is limited by the vocabulary scope and may benefit from dynamic updating using contextual embeddings (e.g., BERT).

E. Comparative Analysis

To validate the performance of the proposed GNN-based sentiment analysis model Table II enhanced with Hill Climbing , we compared it against conventional sentiment analysis models.

The comparative outcomes show the progressive advancements between the conventional and the graphical methods. The classical algorithms of machine learning, like SVM based on the TF-IDF, use only superficial textual characteristics and cannot reflect the more meaningful associations between words, often misunderstanding subtle turns of phrase, like negations or sarcasm. Deep learning architectures, such as CNN-LSTM and CBoW-based hybrids, offer more accurate sequence modelling and feature extraction, but they also have difficulties with modelling more complicated word-to-word dependencies. Combination models comprising statistical and deep features are more accurate but increase computational costs and are very dependent on the datasets.

The proposed GNN with hill climbing optimisation achieves the highest accuracy, wherein the modelling of semantic relationships is based on graph structures, followed by the refinement of parameters. This integration allows the model to accommodate both contextual and relational dependencies. However, the method is also sensitive to how well the graph is made; it is also prone to local optima because the hill-climbing algorithm is greedy, and it can be costly in terms of computation when searching on a large scale. These comments confirm that the suggested model is more accurate and easier to understand, but future research should focus on making it more scalable and applicable to a wider range of datasets.

6. CONCLUSION & FUTURE PERSPECTIVES

This study presents an innovative approach: a sentiment analysis model that integrates graph neural networks (GNNs) with hillclimb optimisation to improve the classification of sentiments in Hindi and Hinglish textual data. The model was able to capture deeper contextual meaning than traditional or sequential models by treating emotion-laden words as graph nodes and their semantic relationships as weighted edges. Using hillclimbing to optimise parameters iteratively made the model even better, resulting in an accuracy of 96.95%, which is higher than traditional methods and close to the best transformer models available, like BERT.

A. Limitations

The efficacy of GNNs in sentiment analysis is significantly correlated with the quality of sentiment graph construction. If the nodes (words) or edges (semantic relationships) are defined or shown incorrectly or incompletely, the graph might not show the real contextual dependence. Such errors could lead to incorrect representations of expressions of sentiment (like how negations or idioms are treated) and mistakes in classification. This sensitivity also makes it harder to scale up for many different datasets, especially in multilingual or code-mixed settings where informal and slang language is common. Although Hill Climbing optimization helped in making our model more robust in fine-tuning the parameters and addressing certain inconsistencies in the graph, the use of static word embeddings and the relationship heuristics could limit generalization to other domains and languages. Also, the performance of the proposed GNN–Hill Climbing model can differ in datasets of different linguistic structure, sentiment distributions, or domain-specific vocabularies. Although our method is efficient in the adaptation to the dataset employed in the present study (Hindi and Hinglish text), it is also dependent on dataset-specific graph construction rules and optimal parameter values, which restricts the ability to generalize. This means that this model might not be easily adopted in other areas or languages without re-training or re-optimization. This kind of sensitivity raises the issue of using contextual embeddings and adaptive methods of optimization in subsequent work to enhance cross- domain ability.

B. Future Work

To overcome such challenges, the future research will be concerned with:

- **Dynamic Graph Construction** – Use of contextual embeddings (e.g., BERT, mBERT) to update edge weights in response to the context, so as to achieve improved semantic coverage of sentiment graphs.
- **Advanced Optimization Techniques** – Evaluating metaheuristics, e.g., Simulated Annealing, Genetic Algorithms, or Reinforcement Learning to surmount the weaknesses of Hill Climbing in escaping local optima.
- **Domain Adaptation** – Developing graph construction plans that can generalize across a wide range of datasets, such as highly code-mixed and multilingual text, thereby making them more scalable.
- **Real-World Applications** - The model can be applied to real-time sentiment monitoring in fields like customer service analytics, social media opinion mining, and emotion-sensitive conversational agents [1].

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AUTHOR CONTRIBUTIONS

Conceptualization, V.Y. and N.D.; methodology, V.Y.; soft- ware, V.Y.; validation, V.Y., N.D., P.V., and A.D.; formal analysis, V.Y.; investigation, V.Y.; data curation, V.Y.; writ- ing—original draft preparation, A.D.; writing—review and editing, V.Y., N.D.,P.V., and A.D.; visualization, V.Y. and P.V.; supervision, P.V.;All authors have read and agreed to the published version of the manuscript.

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