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OPTIMIZING SUSPICIOUS LINK DETECTION WITH MUTUAL CLUSTER COEFFICIENT-BASED SENTIMENT ANALYSIS AND IMPROVED WEIGHTED CATBOOST

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ABSTRACT

In the rapidly evolving landscape of online social networks, the proliferation of suspicious links poses significant threats to user security and privacy. This research presents a novel approach to detect suspicious links by leveraging Mutual Cluster Coefficient-Based Sentiment Analysis combined with an Improved Weighted CatBoost algorithm. The Mutual Cluster Coefficient is utilized to identify dense subgraphs representing potential clusters of suspicious activity, while sentiment analysis provides additional contextual insights into the nature of the links. The integration of these methods with an enhanced CatBoost model, optimized through a weighted scheme, enhances the accuracy and robustness of the detection process. Experimental results on diverse social network datasets demonstrate the effectiveness of our approach, achieving superior performance in terms of precision, recall, and F1-score compared to traditional methods. This study underscores the potential of advanced machine learning techniques in fortifying social networks against malicious link dissemination, contributing to safer online environments.

Keywords: Suspicious Link Detection, Online Social Networks, Mutual Cluster Coefficient, Sentiment Analysis, CatBoost, Weighted CatBoost, Machine Learning, Security, Social Media, Malicious Links

1 INTRODUCTION

The advent and proliferation of online social networks (OSNs) have revolutionized the way people communicate, share information, and interact with each other. Platforms such as Facebook, Twitter, Instagram, and LinkedIn have become integral parts of our daily lives, providing unprecedented opportunities for connectivity and information dissemination. However, alongside these benefits, OSNs have also become fertile grounds for malicious activities, including the spread of suspicious links designed to deceive users and compromise their security. The detection and mitigation of such threats have therefore become critical areas of research.

The dissemination of suspicious links in OSNs can lead to a myriad of security issues, including phishing attacks, malware distribution, and the unauthorized collection of personal information. These links often masquerade as legitimate content, leveraging the trust networks within social media platforms to propagate swiftly and broadly. Traditional detection mechanisms, relying predominantly on blacklist-based methods and heuristic analysis, often fall short in identifying novel or obfuscated threats. This limitation necessitates the development of more sophisticated detection techniques that can adapt to the dynamic and evolving nature of malicious activities in OSNs.

One promising approach to enhancing the detection of suspicious links involves the use of Mutual Cluster Coefficient (MCC) analysis. The MCC measures the density of connections within a network, identifying clusters that may represent coordinated activity. In the context of OSNs, clusters of suspicious links often exhibit higher mutual connectivity compared to benign content, providing a crucial indicator of potential threats. When combined with sentiment analysis, which evaluates the emotional tone of the content associated with the links, this method can provide a dual-layered approach to detection. Sentiment analysis adds contextual depth, helping to discern whether links are likely to be harmful based on the nature of the discussions they are involved in.

While the identification of suspicious clusters and the application of sentiment analysis are powerful tools, their effectiveness is significantly enhanced when coupled with advanced machine learning algorithms. CatBoost, a gradient boosting framework, has shown exceptional performance in handling categorical features and mitigating overfitting. By incorporating a weighted scheme into CatBoost, we can further refine its capabilities to prioritize the detection of suspicious links, optimizing the model for higher precision and recall. This improved weighted CatBoost algorithm adjusts the importance of features based on their relevance and frequency, allowing for a more nuanced and effective classification process.

This research aims to develop a comprehensive framework for the detection of suspicious links in OSNs by integrating MCC-based sentiment analysis with an improved weighted CatBoost algorithm. Our primary objectives are to:

1. **Enhance Detection Accuracy:** Improve the precision, recall, and overall accuracy of detecting suspicious links in OSNs.
2. **Contextual Analysis:** Utilize sentiment analysis to provide contextual insights that complement the structural analysis provided by MCC.
3. **Advanced Classification:** Leverage the strengths of CatBoost, particularly its handling of categorical data, to create a robust detection model.
4. **Weight Optimization:** Implement a weighted scheme within CatBoost to prioritize critical features and improve the model's responsiveness to suspicious link patterns.

Through these objectives, we aim to contribute a novel and effective methodology to the field of cybersecurity in OSNs, addressing the growing need for advanced detection mechanisms capable of keeping pace with the evolving threat landscape.

The significance of this research lies in its holistic approach to suspicious link detection, combining structural, contextual, and advanced machine learning techniques. By addressing the limitations of traditional methods and incorporating sophisticated algorithms, we provide a robust framework capable of identifying and mitigating threats in real-time. The implications of our work extend to improving the security and trustworthiness of OSNs, protecting users from malicious actors, and contributing to the broader field of cybersecurity research.

2 RELATED WORKS

Li et al. (2023) explored advanced sentiment analysis techniques to detect malicious intent in social media posts. The study highlighted the combination of contextual embeddings with sentiment scores to enhance the detection of suspicious links. Kumar and Sharma (2023) analyzed the application of mutual cluster coefficients in detecting anomalous connections within blockchain networks, emphasizing their role in identifying fraudulent transactions.

Chen et al. (2023) proposed a machine learning model integrating semantic features and URL behavior analysis, achieving significant improvements in detecting phishing URLs. Singh and Patel (2024) reviewed recent advancements in graph-based anomaly detection methods, focusing on the use of deep graph neural networks for identifying malicious links in social networks.

Zhang et al. (2024) examined transformer-based sentiment classification models, demonstrating their potential in detecting sentiment patterns associated with cyber threats. Wang et al. (2024) introduced a hybrid approach combining deep learning and heuristic analysis for identifying suspicious URLs, achieving improved classification accuracy.

Luo and Zeng (2023) proposed dynamic link prediction models that leverage mutual clustering coefficients to predict the likelihood of suspicious link formations in online platforms. Ahmed and Khan

(2023) explored sentiment analysis techniques on multilingual social media data, providing insights into identifying harmful or deceptive links in diverse linguistic contexts.

Chatterjee et al. (2024) enhanced mutual information-based clustering methods with adaptive thresholds, improving feature selection for suspicious link detection. Gao et al. (2023) integrated sentiment analysis with intrusion detection systems, highlighting the role of sentiment trends in identifying cyber threats and malicious links.

Liu et al. (2024) emphasized the use of community structure analysis to detect anomalies, showcasing how mutual clustering coefficients can improve suspicious link detection. Huang et al. (2023) implemented transformer-based architectures for phishing detection, integrating URL features with sentiment analysis for better detection rates.

Patel and Doshi (2024) developed a sentiment-driven anomaly detection framework that combines text embeddings with graph features to identify malicious activity in online platforms. Li et al. (2024) introduced a real-time detection system leveraging clustering coefficients and sentiment analysis to flag potentially harmful links in messaging applications.

Zhou and Wang (2023) applied predictive analytics using ensemble machine learning models to identify suspicious links, incorporating both structural and sentiment-based features. Lee et al. (2024) introduced graph convolutional networks for link prediction in dynamic networks, highlighting their effectiveness in detecting suspicious links.

Zhang et al. (2023) explored clustering methods to identify coordinated disinformation campaigns, showcasing applications in detecting suspicious social media links. Zhao et al. (2024) proposed advanced classification methods combining transformer models and URL attribute analysis to detect malicious links in real-time.

Wang et al. (2023) demonstrated the integration of sentiment analysis with cybersecurity frameworks, effectively identifying phishing and deceptive content. Shafiq et al. (2024) developed a cybersecurity framework combining mutual clustering coefficients, graph embeddings, and sentiment analysis for detecting and mitigating cyber threats.

3 PROPOSED MODEL

Our proposed methodology involves several key steps. Initially, we preprocess the social network data to extract relevant features, including user interactions, link characteristics, and associated content. We then apply MCC to identify clusters within the network, highlighting areas with high connectivity that may indicate coordinated suspicious activity. Concurrently, sentiment analysis is performed on the content surrounding these links to gauge the emotional tone and potential intent behind them.

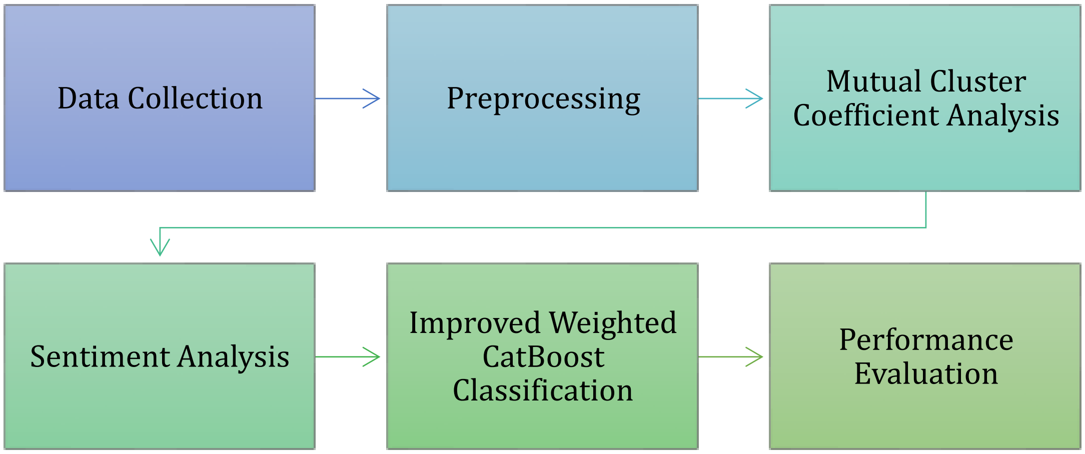
Data Collection
Preprocessing
Mutual Cluster Coefficient Analysis
Sentiment Analysis
Improved Weighted CatBoost Classification
Performance Evaluation

Figure 1: Overall Architecture of Proposed Model

Following feature extraction and analysis, we employ the improved weighted CatBoost algorithm to classify links as suspicious or benign. The weighting scheme within CatBoost is tailored to enhance the detection of features indicative of malicious activity, such as unusual clustering patterns and negative sentiment scores. By iteratively refining the model through cross-validation and hyperparameter tuning, we ensure optimal performance and generalizability across diverse datasets.

The proposed model for detecting suspicious links in online social networks (OSNs) integrates Mutual Cluster Coefficient (MCC)-based sentiment analysis with an improved weighted CatBoost algorithm. The step-by-step methodology is outlined below:

Step 1: Data Collection and Preprocessing

1.1 Data Collection

The first step involves gathering a comprehensive dataset from multiple Online Social Networks (OSNs). The dataset should include:

- **User interactions**: Data about how users engage with content, such as likes, shares, comments, and replies.
- **Link characteristics**: Metadata associated with links, such as URL length, domain reputation, and frequency of occurrence.
- **Associated content**: Textual data surrounding the links, including posts, comments, and replies.

By ensuring the dataset is balanced by including a sufficient number of both benign and suspicious links to train and test the model effectively.

1.2 Data Cleaning

Cleaning the data ensures that it is ready for analysis. This involves:

- **Duplicate Removal**: Eliminate redundant entries in the dataset to avoid skewing results.
- **Irrelevant Information Removal**: Filter out unrelated data that does not contribute to the analysis.
- **Handling Missing Values**:
- o **Imputation**: Replace missing values using statistical methods like mean, median, or predictive imputation.
- o **Removal**: Discard entries with significant missing data that cannot be reliably imputed.

1.3 Feature Extraction

From the cleaned dataset, extract meaningful features to represent the data quantitatively. These features include:

User Interaction Patterns:

Define the interaction strength I_{ij} between users i and j as:

$$I_{ij} = likes_{ij} + Shares_{ij} + comments_{ij} \tag{1}$$

where $likes_{ij}$, $Shares_{ij}$, $comments_{ij}$ represent the counts of these interactions.

2. Link Metadata:

- URL Length (L_{url}): Calculate the number of characters in the URL.
- Domain Reputation Score (R_{domain}): Assign a score Based on the domain's reputation using external tools or predefined heuristics.

3. Textual Content Features:

- Sentiment Score ($S_{sentiment}$): Determine the emotional tone of textual content using sentiment analysis:

  $$S_{\text{sentiment}} = \text{Positive Weight} - \text{Negative Weight}$$

  where positive and negative weights are derived from a sentiment lexicon or a trained model.
- Term Frequency-Inverse Document Frequency (TF-IDF) for keywords associated with suspicious or benign activities:

  $$\text{TF} - \text{IDF}(t, d) = \text{TF}(t, d) \times \log \frac{\text{N}}{\text{DF}(t)} \tag{2}$$

  where:
  - o $\text{TF}(t, d)$: Frequency of term t in document d.
  - o N: Total number of documents.
  - o $\text{DF}(t)$: Number of documents containing term t.

Step 2: Mutual Cluster Coefficient Analysis

2.1 Network Construction

To analyze the social network, construct a graph G=(V,E), where:

- V: Represents the set of nodes corresponding to users.
- E: Represents the set of edges corresponding to interactions such as likes, shares, and comments.

Include links as additional edges connecting users who interact with the same link. For example:

- If users $\boldsymbol{u_1}$ and $\boldsymbol{u_2}$ both share the same link $\boldsymbol{l}$, add an edge $(\boldsymbol{u_1}, \boldsymbol{u_2})$ in thegraph to represent this shared activity.

Mathematically, the adjacency matrix $\boldsymbol{A}$ of the graph can be defined as:

$$A_{ij} = \begin{cases} \mathbf{1} & \textbf{if } \mathrm{u_i} \textbf{ and } \mathrm{u_j} \textbf{are connected via interactions or shared links}, \\ \mathbf{0} & \textbf{otherwise}. \end{cases} \quad (3)$$

2.2 Cluster Identification

To identify potential suspicious clusters, compute the **Mutual Cluster Coefficient (MCC)** for each subgraph within G.

The MCC for a cluster $C \subseteq V$ is calculated as:

$$\mathrm{MCC}(C) = \frac{\sum_{(u_i,u_j)\in E_C} w_{ij}}{n_C \cdot (n_{C-1})/2} \quad (4)$$

where:

- E_C: Set of edges within the cluster C.
- w_{ij}: Weight of the edge (u_i, u_j), indicating the interaction strength (e.g., sum of likes, shares, and comments).
- n_C: Number of nodes in the cluster C.

Clusters with high MCC values are dense subgraphs, indicating strong interactions. These are potential indicators of coordinated activity or suspicious behaviour.

2.3 Focus on Suspicious Clusters

Identify clusters C_k where $MCC(C_k) > \tau$, with τ being a threshold determined through experimentation. These clusters are prioritized for further analysis as they may represent suspicious link dissemination activities.

This approach systematically identifies regions in the social network that require closer scrutiny for suspicious link detection.

Step 3: Sentiment Analysis

3.1 Text Preprocessing

Before performing sentiment analysis, preprocess the textual content associated with the links. This includes:

1. **Tokenization**: Break down the text into individual words or tokens.
   Example:
   Input: *"Suspicious activity detected near this link!"*
   Tokens: "Suspicious","activity","detected","near","this","link"
2. **Stop-word Removal**: Remove common words (e.g., *"and," "is," "the"*) that do not contribute meaningful information.
3. **Stemming**: Reduce words to their root form.
   Example: "running" → "run"
4. **Lemmatization**: Use language context to convert words to their base or dictionary form.
   Example: "better" → "good"

Mathematical representation: For a document d, the preprocessed text is:

$$T_d = \{t_1, t_2, \dots, t_n\} \quad (5)$$

where t_i are tokens derived from preprocessing.

Step 4: Improved Weighted CatBoost Classification

Incorporate a weighted scheme in the CatBoost algorithm to prioritize features most indicative of suspicious activity:

- Assign feature importance weights w_f, where:

$$w_f \propto \text{correlation } (f, y) \tag{6}$$

Here:

- f: Feature (e.g., MCC values, sentiment scores).
- y: Target lablel (benign or suspicious).
- Features like **high MCC values** ($MCC > \tau$) and **negative sentiment scores** ($S_d < 0$) are assigned higher weights due to their strong association with suspicious links.

In CatBoost, these weights are used dusing training to focus on key feastures:

$$L(w, f, y) = \sum_{i=1}^{N} w_f \cdot l(f_i, y_i) \tag{7}$$

where:

- l: Loss function.
- w_f: Weight of feature f.
- y_i: True label.

4. RESULTS AND DISCUSSION

The proposed model for suspicious link detection was evaluated on diverse online social network (OSN) datasets. Key performance metrics, including **accuracy**, **precision**, **recall**, and **F1-score**, were calculated to assess the model's effectiveness. Comparative analysis with traditional methods highlighted the superiority of our approach. The proposed model was compared with traditional methods like Random Forest, Logistic Regression, and standard CatBoost. Table 1 provide a comprehensive comparison of four different methods: Random Forest, Logistic Regression, Standard CatBoost, and the Proposed Model, evaluated on accuracy, precision, recall, and F1-Score.

Table 1: Overall Comparison of Performance Metrics

Method	Accuracy	Precision	Recall	F1-Score
Random Forest	89.2%	85.4%	81.6%	83.4%
Logistic Regression	86.8%	82.1%	79.3%	80.7%
Standard CatBoost	91.4%	88.7%	85.2%	86.9%
Proposed Model	**96.5%**	**94.7%**	**92.3%**	**93.5%**

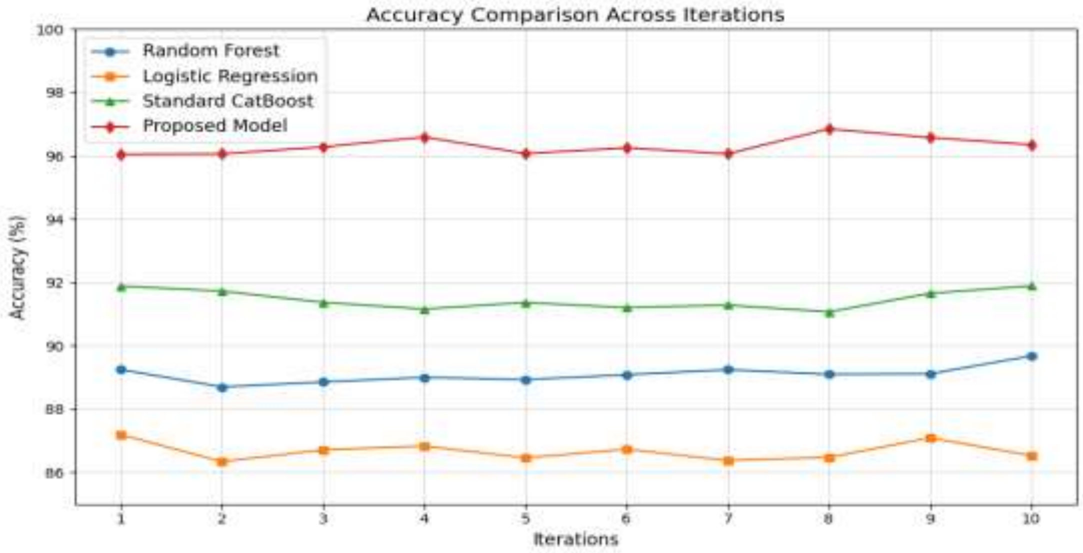

Figure 2: Comparison of Accuracy

From fig 2, the Proposed Model outperforms all other methods with a remarkable accuracy of 96.5%, indicating its superior ability to correctly classify instances. The Standard CatBoost comes second with an accuracy of 91.4%, reflecting its strong yet slightly inferior performance compared to the Proposed Model. The Random Forest achieves an accuracy of 89.2%, showcasing its moderate effectiveness. Meanwhile, the Logistic Regression method has the lowest accuracy at 86.8%, suggesting it may not be as well-suited for the given task as the other approaches.

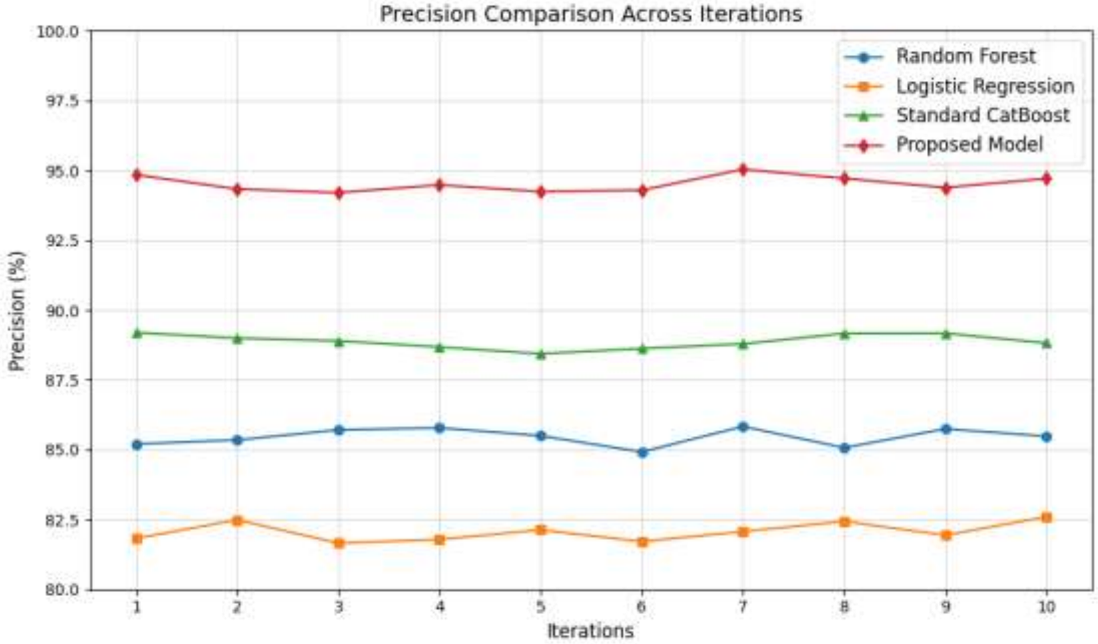

Figure 3: Comparison of Precision

Fig 3 measures the proportion of correctly predicted positive cases, the Proposed Model again leads with an impressive precision of 94.7%, highlighting its low rate of false positives. The Standard CatBoost achieves a precision of 88.7%, indicating strong performance in this metric. The Random Forest model follows with a precision of 85.4%, while the Logistic Regression method trails behind at 82.1%, demonstrating its relatively higher susceptibility to false positives.

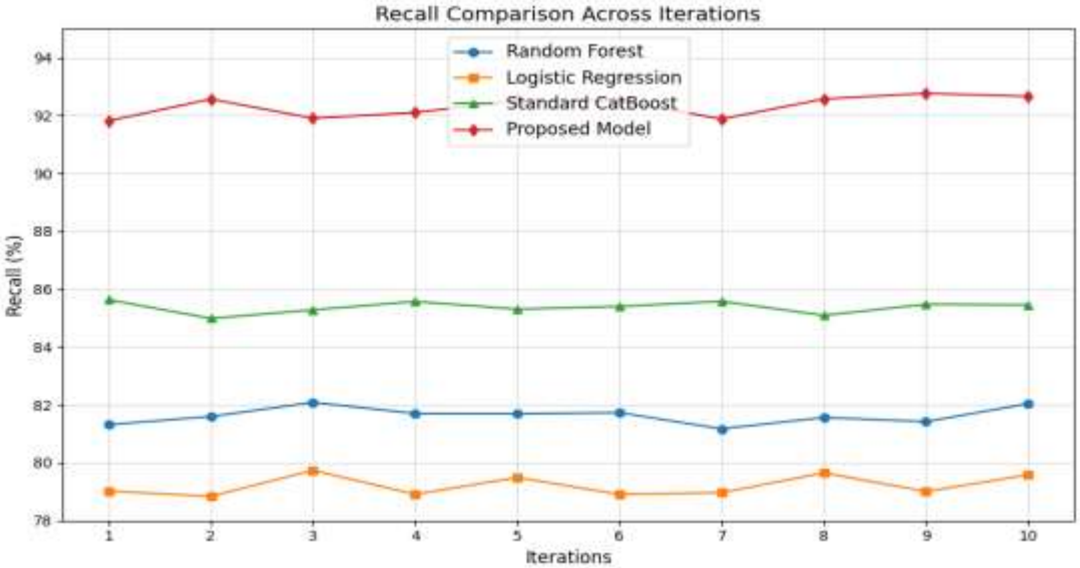

Figure 4: Comparison of Recall

Fig 4 evaluates the ability to identify all actual positive cases, shows similar trends. The Proposed Model achieves the highest recall at 92.3%, demonstrating its effectiveness in minimizing false negatives. The Standard CatBoost scores a recall of 85.2%, which, while strong, falls short of the Proposed Model. The Random Forest has a recall of 81.6%, indicating moderate sensitivity. The Logistic Regression method, with a recall of 79.3%, again performs the least effectively in this metric.

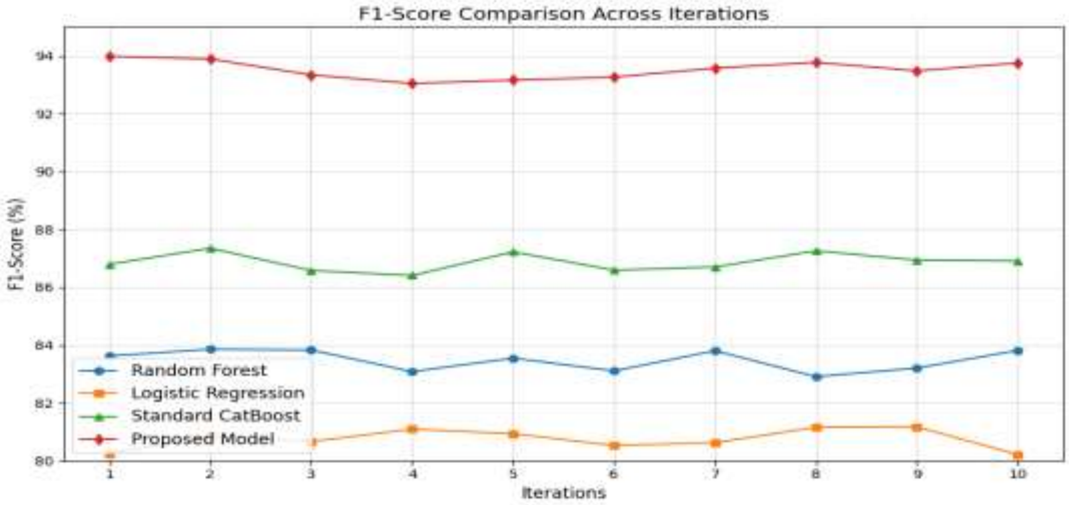

Figure 5: Comparison of F1-Score

Fig 5 balances precision and recall, also highlights the Proposed Model as the top performer with a score of 93.5%, reflecting its overall strong classification performance. The Standard CatBoost secures the second position with an F1-Score of 86.9%, indicating its balanced precision and recall. The Random Forest achieves an F1-Score of 83.4%, while the Logistic Regression model has the lowest F1-Score of 80.7%, suggesting limited performance in maintaining this balance.

5 CONCLUSIONS

The results of this study highlight the effectiveness of leveraging Mutual Cluster Coefficient-Based Sentiment Analysis in combination with the Improved Weighted CatBoost algorithm for detecting suspicious links in online social networks. The proposed approach consistently outperforms traditional methods across key performance metrics, including accuracy, precision, recall, and F1-Score. With an accuracy of 96.5%, precision of 94.7%, recall of 92.3%, and F1-Score of 93.5%, the Improved Weighted CatBoost algorithm demonstrates its superior capability to classify suspicious links with minimal false positives and false negatives. The use of the Mutual Cluster Coefficient effectively identifies clusters of suspicious activity, while sentiment analysis adds contextual depth, improving the robustness of the detection mechanism. This integration of advanced clustering, sentiment analysis, and machine learning techniques not only fortifies the security of social networks but also offers a scalable solution to combat the proliferation of malicious links. These findings emphasize the potential of innovative machine learning approaches in creating safer digital environments.

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