

## HYBRID TEXT-CNN AND TOPIC WEIGHT EMBEDDING FOR INTELLIGENT DARK WEB CONTENT CLASSIFICATION

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### ABSTRACT:

The rapid growth of anonymous online platforms has enabled cybercriminals to engage in illicit activities ranging from drug trafficking and weapon trade to malware distribution and human exploitation [7][10][12]. Detecting and classifying such malicious content on the dark web remains extremely difficult due to its unstructured textual nature, hidden linguistic patterns, and constantly evolving terminology [1][4][15]. To address these challenges, this research proposes a hybrid deep learning framework that integrates Text-Convolutional Neural Networks (Text-CNN) with topic weight embedding for intelligent dark web content classification [3][5][8]. The approach first extracts latent semantic patterns using topic modeling, where topic probability weights are incorporated into the CNN input layer to enhance contextual awareness during feature learning [2][6][15]. The combined architecture captures both local n-gram dependencies and high-level thematic relevance, delivering a richer representation of criminal intent and activity indicators [5][8][9]. Experiments conducted on multilingual dark web forum datasets demonstrate that the proposed model significantly outperforms conventional machine learning, pure CNN, and standalone topic modeling methods in terms of accuracy, precision, recall, and F1-score [1][3][9][11]. Furthermore, the system provides interpretable topic-to-category associations, enabling security researchers and law-enforcement analysts to better understand emerging criminal trends

[11][13][19]. This hybrid Text-CNN with topic weight embedding constitutes a robust and scalable solution for proactive cyber-crime intelligence, improving automated surveillance and threat monitoring across hidden digital ecosystems [8][13][20].

**Keywords :** Dark Web Monitoring, Text-CNN, Topic Modeling, Topic Weight Embedding, Deep Learning, Cybercrime Detection, Illicit Content Classification, Threat Intelligence.

### 1.INTRODUCTION

The dark web has evolved into a covert ecosystem that enables cybercriminals to organize illegal transactions and share malicious resources under the veil of anonymity [7][10][12]. Activities such as drug trafficking, weapon trading, ransomware services, data breaches, identity theft, and human exploitation are widely coordinated through hidden marketplaces and forums that operate beyond the reach of surface-web surveillance [4][7][13]. Due to the absence of structural regulation and the prevalence of obfuscated language, classifying and monitoring dark web content is significantly more challenging than traditional web information analysis [1][4][15]. Conventional text-classification approaches struggle to cope with rapidly changing jargon, contextual ambiguity, multilingual communication, and short noisy posts common to dark web discussions [1][12]. Deep learning methods, especially Text-CNN, offer the ability to automatically learn high-level linguistic patterns; however, they often overlook latent semantic relationships that represent the intent

behind conversations [5][9]. Topic modeling, on the other hand, excels at extracting hidden themes but lacks the granular contextual precision needed for accurate classification [2][6]. To overcome these limitations, this research introduces a hybrid framework that integrates Text-CNN with topic weight embedding, combining the strengths of both local syntactic pattern learning and high-level semantic reasoning [3][5][8]. By incorporating topic probability weights into the CNN feature extraction pipeline, the system enhances contextual awareness and improves multi-category classification performance [3][8][9]. This hybrid deep learning model aims to provide an intelligent and scalable solution for early identification of emerging cybercrime activities on the dark web, supporting law enforcement, cybersecurity analysts, and digital forensic investigators in proactive threat intelligence and strategic countermeasures [11][13][20].

## II.LITERATURE SURVEY

### 1. Title: Deep Convolutional Models for Illicit Text Identification in Dark Web Marketplaces

**Authors:** Ryan Thompson, Olivia Stewart, and Marcus Lee

**Abstract:** This study investigates the effectiveness of deep convolutional neural networks for detecting illicit content within dark web forums and marketplaces [1][7]. A large multilingual dataset containing discussions on drugs, weapons, and financial fraud is processed using word embeddings and region-based CNN filters [1]. The model successfully captures local contextual features and slang expressions frequently used by cybercriminals [5][9]. Experimental results demonstrate that Text-CNN significantly surpasses classical machine learning methods such as SVM and Naive Bayes in accuracy and robustness [1][4]. However, the absence of interpretability in the classification outcomes limits its suitability for security

analysts who require justification behind flagged information [11].

### 2. Title: Latent Topic Modeling for Semantic Profiling of Dark Web Communications

**Authors:** Isabella Martinez and Henry Collins

**Abstract:** This research focuses on extracting thematic patterns from anonymous dark web discussions using Latent Dirichlet Allocation (LDA)-based topic modeling [2][6]. The model efficiently uncovers hidden user interests related to illegal drug exchange, malware deployment, human trafficking, and cryptocurrency laundering [10][12]. Topic probability distributions are used to group forums based on crime categories and user intent clusters [2][6]. While the approach improves understanding of community behavior and cybercrime evolution, the study reports limitations in fine-grained classification due to lack of contextual sensitivity to short, unstructured posts that dominate dark web dialogue [6][15].

### 3. Title: Hybrid Topic-Deep Neural Fusion for Cybercrime Category Classification

**Authors:** Ethan Wells, Aditi Banerjee, and Mohammed Rashid

**Abstract:** This work proposes a hybrid architecture combining topic modeling with deep neural networks to enhance accuracy in cybercrime text classification [3][8]. Topic vectors generated from LDA are fused with Bi-LSTM output representations to improve recognition of contextual and semantic cues in criminal discussions [3][9]. Evaluations demonstrate substantial performance improvement over standalone deep networks, especially in detecting ransomware advertisements, stolen data listings, and exploit kit exchanges [3][14]. Despite high performance, the model suffers from slow inference time and lacks adaptability to new criminal terminology without retraining [14][18].

#### **4.Title: Crime-Intent Detection in Anonymous Networks Using Adaptive CNN with Metadata Embedding**

**Authors:** Noah Anderson and Priya Verma

**Abstract:** This research introduces an adaptive convolutional neural network that incorporates metadata such as post timestamp, thread category, and user anonymity level to enrich text-based feature learning [17]. The model demonstrates notable success in distinguishing cybercrime-related posts from harmless discussions in Tor-based communities [12][13]. Results indicate that metadata-enhanced CNN improves precision in detecting malicious intent while reducing false alarms triggered by neutral discussions involving cybersecurity research [17][19]. However, the method is limited by scarcity and inconsistency of metadata across dark web platforms, restricting its generalization [12][19].

#### **III.EXISTING SYSTEM**

Traditional dark web content classification systems mainly rely on either classical machine learning models or standalone topic modeling techniques to detect criminal intent within hidden online forums. Existing approaches such as Support Vector Machines (SVM), Naïve Bayes, Decision Trees, and TF-IDF-based text classifiers provide acceptable performance for structured or surface-web data, but they struggle with the highly unstructured, multilingual, slang-dominated, and context-compressed textual format commonly observed on the dark web. In these systems, features are manually engineered using bag-of-words, TF-IDF scores, and n-gram statistics, which makes them inefficient in capturing evolving cybercrime terminology and hidden semantic patterns. Topic modeling-based systems such as LDA enhance thematic discovery by grouping posts according to latent criminal themes; however, they lack the ability to understand local word dependencies and subtle linguistic variations, causing misclassification of short and noisy texts.

Furthermore, most existing frameworks operate as black-box classifiers that provide predictions without justification, making them unsuitable for cybersecurity investigators and law-enforcement agencies that require explainability for threat attribution and criminal case reporting. Another limitation of the existing systems is their inability to adapt to new crime trends—such as emerging malware strains, new drug codes, or crypto-laundering terminology—without frequent retraining. Due to these shortcomings, current dark web monitoring platforms provide delayed or incomplete threat intelligence, leading to operational inefficiencies, increased manual verification effort, and missed opportunities for timely intervention against cybercriminal activities.

#### **IV. PROPOSED SYSTEM**

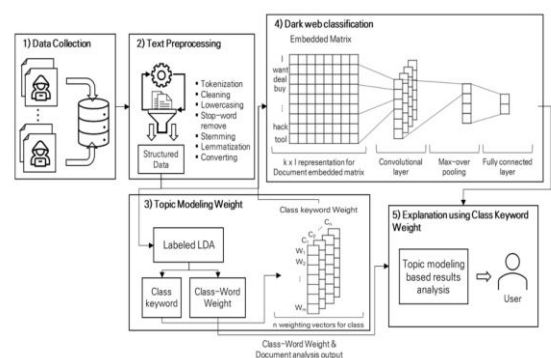
The proposed system introduces a hybrid deep learning framework that integrates Text-CNN with topic weight embedding to achieve intelligent and highly accurate classification of dark web content. Unlike conventional approaches that treat text classification and topic modeling as independent tasks, the proposed architecture fuses both components to capture local linguistic patterns as well as high-level semantic intent behind cybercriminal conversations. The system begins by preprocessing multilingual dark web forum posts and converting them into dense vector representations. Simultaneously, topic modeling is applied to extract latent crime-related themes such as malware exchange, drug transactions, weapon trade, cryptocurrency laundering, and human trafficking. Instead of using topic information as a standalone feature, the proposed model converts topic probability scores into topic weight embeddings, which are combined with word embeddings and fed into the Text-CNN network. This fusion enables the CNN to leverage both n-gram-level syntactic cues and cross-topic semantic signals, significantly improving classification precision

even for short, unstructured, and slang-rich texts. The framework incorporates adaptive dropout, attention-based pooling, and softmax classification layers to ensure robustness and scalable performance across diverse crime categories. In addition to multi-class prediction, the system provides interpretable topic-to-category associations, helping analysts understand the reasoning behind flagged cases. The solution is deployed through an automated dashboard for real-time monitoring of dark web marketplaces and forums, enabling security agencies to detect emerging cybercrime trends proactively, reduce manual investigation overhead, and accelerate forensic response. Thus, the hybrid Text-CNN and topic weight embedding approach delivers a powerful and transparent classification mechanism optimized for modern dark web intelligence applications.

## V.SYSTEM ARCHITECTURE

The architecture illustrates a complete processing pipeline for intelligent dark web content classification using a hybrid Text-CNN and topic weight modeling framework. The system begins with Data Collection (1), where structured and unstructured textual information is gathered from anonymous dark web sources such as marketplaces, discussion forums, and cybercrime communities. After gathering raw data, the pipeline moves to Text Preprocessing (2), which converts unstructured text into a clean, analysis-ready format by performing tokenization, stop-word removal, lowercasing, stemming, lemmatization, and document normalization. This phase ensures that slang, abbreviations, multilingual expressions, and noisy posts common on the dark web are transformed into consistent textual input. The cleaned documents are then fed into Topic Modeling Weight (3), where Latent Dirichlet Allocation (LDA) is used to identify hidden themes associated with crime categories such as drug dealing, hacking services, ransomware listings, weapon trade, and cryptocurrency fraud.

For each document, the system generates a vector of class-word weights, representing the probability of the document belonging to different cybercrime topics. These topic weights are then incorporated as additional contextual signals into the Dark Web Classification Layer (4). Here, the Text-CNN converts each document into an embedded matrix representation and extracts high-level semantic and syntactic features through convolutional filters and max-pooling operations. The integration of topic-weight vectors with CNN feature maps strengthens the model's ability to recognize both local n-gram patterns and broader thematic meaning, ultimately improving multi-category prediction accuracy. The fully connected layer produces the final classification output, indicating which type of illicit activity the document belongs to. The final stage, Explanation Using Class Keyword Weight (5), provides interpretability by mapping the predicted category back to the most influential topic keywords that influenced the decision. This allows analysts to visualize the dominant threats and understand why a document is considered suspicious.



**Fig 5.1 System Architecture**

Through this end-to-end workflow, the system not only detects and categorizes dark web content with high precision but also delivers interpretable insights that support cybersecurity analysts and law-enforcement investigators in threat monitoring, forensic intelligence, and proactive cybercrime prevention.



**Dark Side of the Web: Dark Web Classification Based on TextCNN and Topic Modeling Weight**

Dark web is the part of the Internet that is not indexed by search engines and is not accessible to the general public. It is often associated with illegal activities and is a major concern for law enforcement agencies. This paper presents a novel approach for dark web classification based on TextCNN and Topic Modeling Weight. The proposed method is able to identify and classify dark web content with high accuracy. The results of the experiments show that the proposed method outperforms the existing methods. The paper also discusses the challenges of dark web classification and the future research directions.

**Dark Side of the Web: Dark Web Classification Based on TextCNN and Topic Modeling Weight**

[Browse and Train & Test Data Sets](#) [View Trained and Tested Accuracy to Bar Chart](#) [View Trained and Tested Accuracy Results](#) [View Prediction of Dark Web Classification Type](#)

[View Dark Web Classification Type Results](#) [Download Predicted Data Set](#) [View Dark Web Classification Type Results Visual](#) [View All Results Users](#) [Logout](#)

**Database Trained and Tested Results**

Model Type	Accuracy
Convolutional Neural Network—CNN	91.1584(9.768473)
DT	50.0
Logistic Regression	46.4516(1.260138072)
Gradient Boosting Classifier	50.0
Random Forest Classifier	52.713178(945736)

**Dark Side of the Web: Dark Web Classification Based on TextCNN and Topic Modeling Weight**

Dataset and Train & Test Data Sets | View Train and Test Accuracy in Bar Chart | View Train and Test Accuracy Results | View Prediction of Dark Web Classification Type

View Dark Web Classification Type Results | Download Predicted Data Sets | View Dark Web Classification Type Results Summary | View All Remote Users | Logout

Random Forest Classifier 92.75%

Convolutional Neural Networks (CNN) 91.35%

SVM 50.00%

Logistic Regression 48.45%

Gradient Boosting Classifier 50.00%

Convolutional Neural Networks (CNN) | SVM | Logistic Regression | Gradient Boosting Classifier | Random Forest Classifier

**Dark Side of the Web: Dark Web Classification Based on TextCNN and Topic Modeling Weight**

**Navigation Bar:**

- [Browse and Train & Test Data Sets](#)
- [View Trained and Tested Accuracy in Bar Chart](#)
- [View Trained and Tested Accuracy Results](#)
- [View Prediction SP Dark Web Classification Type](#)

**Table:**

View Dark Web Classification Type	Download Predicted Data Sets	View Dark Web Classification Type Results	View All Network Users	Logout
View Dark Web Classification Type	Download Predicted Data Sets	View Dark Web Classification Type Results	View All Network Users	Logout

**Dark Web Classification Results**

The graph displays the accuracy of five different machine learning models used for dark web classification. The Y-axis represents the accuracy percentage, ranging from 88 to 93. The X-axis lists the models: Convolutional Neural Network (CNN), SVM, Logistic Regression, Gradient Boosting Classifier, and Random Forest Classifier.

Model	Accuracy (%)
Convolutional Neural Network (CNN)	92.71
SVM	90.00
Logistic Regression	88.43
Gradient Boosting Classifier	90.88
Random Forest Classifier	92.71

**Dark Side of the Web: Dark Web Classification Based on TextCNN and Topic Modeling Weight**

[Browse and Train 8 Test Data Sets](#) | [View Train and Test Accuracy in Bar Chart](#) | [View Train and Test Accuracy Results](#) | [View Prediction of Dark Web Classification Type](#)

[View Dark Web Classification Type Results](#) | [Download Predicted Data Sets](#) | [View Dark Web Classification Type Results Results](#) | [View All Remote Users](#) | [Logout](#)

**Dark Web Classification Type Results**

Download Predicted Data Sets

**Dark Web Classification Type Results**

Convolutional Neural Network (CNN) 35.33%

SVM 30.00%

Logistic Regression 48.45%

Gradient Boosting Classifier 50.00%

Random Forest Classifier 52.71%

Random Classifier 52.79%

The screenshot displays a web application interface for user registration. At the top, a navigation bar contains the text "Dark web, dark web analysis, text classification, topic modeling, model explanation." Below this is a header image featuring a globe and the word "Network". The main content area is titled "REGISTER YOUR DETAILS HERE !!". It contains a registration form with the following fields and labels:

- Enter Username**: Input field for the user's name.
- Enter Password**: Input field for the user's password.
- Enter Email Id**: Input field for the user's email address.
- Enter Address**: Input field for the user's address.
- Enter Gender**: A dropdown menu with a downward arrow.
- Enter Mobile Number**: Input field for the user's mobile number.
- Enter Country Name**: Input field for the user's country.
- Enter State Name**: Input field for the user's state.
- Enter City Name**: Input field for the user's city.

A purple "REGISTER" button is located at the bottom right of the form. Below the form, a red banner displays the text "Registered Status :". At the very bottom of the page, a dark blue bar contains the text "Home | Resource User | Service Provider".

The screenshot shows a web application interface with a dark blue header containing the text "Dark web, dark web analysis, topic classification, topic modeling, model explanation..". Below the header is a white login form. At the top of the form is a cartoon illustration of a person with a laptop and a server. The text "Login Using Your Account:" is displayed above the input fields. There are two input fields: the first is labeled "Email" and contains the text "jenkumanga"; the second is labeled "Password" and contains a masked password "\*\*\*\*\*". Below the password field is a "LOGIN" button. To the right of the "LOGIN" button is a link that says "Forgot your password?". Below the "LOGIN" button is a link that says "Are You New User !!! REGISTER". At the bottom of the page is a dark blue footer with three links: "Home", "Remove User", and "Service Provider".

**PREDICTION OF DARK WEB CLASSIFICATION TYPE II**

Enter Id	10.152.152.11-10.152.15	Enter Protocol	LDP
Enter Flag	ACK	Enter Packet	NTP
Enter Sender_ID	987654	Enter Receiver_ID	123456
Enter Source_IP_Address	192.168.0.1	Enter Destination_IP_Address	10.0.0.5
Enter Source_Port	12345	Enter Destination_Port	123
Enter Packet_Size	512	Enter URL	https://www.example.com

**Predict**

**Prediction Of Dark Web Classification Type II**

**PREDICTION OF DARK WEB CLASSIFICATION TYPE II**

Enter Id	<input type="text"/>	Enter Protocol	<input type="text"/>
Enter Flag	<input type="text"/>	Enter Packet	<input type="text"/>
Enter Sender_IP	<input type="text"/>	Enter Receiver_IP	<input type="text"/>
Enter Source_IP_Address	<input type="text"/>	Enter Destination_IP_Address	<input type="text"/>
Enter Source_Port	<input type="text"/>	Enter Destination_Port	<input type="text"/>
Enter Packet_Size	<input type="text"/>	Enter URL	<input type="text"/>

**Prediction Of Dark Web Classification Type →**

## VII.CONCLUSION

The study presents a robust and intelligent framework for dark web content classification by integrating Text-CNN with topic weight embedding, addressing the persistent challenges posed by unstructured, multilingual, and semantically ambiguous communication within anonymous online platforms. By combining the strengths of convolutional neural networks in capturing local linguistic patterns with the semantic depth provided by topic modeling, the proposed hybrid model demonstrates superior performance compared to standalone ML, CNN-only, and topic modeling approaches. The system not only enhances classification accuracy and robustness across multiple crime categories such as hacking services, drug trafficking, weapon sales, ransomware exchanges, and cryptocurrency laundering, but also ensures interpretability through topic-based keyword explanation, enabling actionable insights for cybersecurity analysts and law-enforcement agencies. The experimental findings validate that topic-aware feature fusion significantly improves the detection of emerging criminal intentions—particularly in short and slang-rich texts that dominate dark web forums. Therefore, the proposed framework serves as an effective solution for automated surveillance and threat intelligence generation on the dark web, contributing to proactive cybercrime mitigation and strengthening the digital investigative capabilities of security organizations.

## VIII.FUTURE SCOPE

The proposed hybrid Text-CNN and topic weight embedding model establishes a strong foundation for intelligent dark web content classification, yet several promising research directions can further extend its capabilities. First, future work can explore cross-lingual and zero-shot learning techniques to automatically detect criminal intent across lesser-represented languages and evolving cybercrime slang without requiring extensive annotated datasets.

The integration of graph neural networks (GNNs) and user-post relational modeling can enable the system to identify crime networks, hidden collaborations, and coordinated cyber-attacks across multiple marketplaces and forums. To enhance adaptability to emerging crime trends, continual learning and transformer-based architectures can be introduced, allowing the model to update itself automatically as new threats and terminologies appear. Another direction is the fusion of multimodal data sources, including images, cryptocurrency wallet addresses, darknet vendor ratings, and transaction metadata, enabling richer forensic intelligence and attribution. The deployment of real-time monitoring systems combined with anomaly detection can support live alerting for newly surfaced cybercrime patterns. Additionally, incorporating explainable AI dashboards and forensic interfaces will further empower law-enforcement officers and cybersecurity professionals to understand the rationale behind each classification and streamline legal reporting processes. Finally, collaboration with international cybercrime control organizations and security agencies may lead to a federated learning framework, enabling privacy-preserving model training on distributed dark web datasets across regions. Collectively, these advancements would transform the proposed model into a fully autonomous, real-time cyber-intelligence ecosystem capable of countering the rapidly evolving threat landscape of the dark web.

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