Explicit Image and Malicious URL Detection for Social Media Platforms: A Hybrid Approach Using Skin Tone Analysis, Object Detection, and Random Forest

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***Abstract*—The rapid growth of social media, from 4.2 billion users in January 2021 to 4.62 billion in January 2022, has amplified concerns over explicit content and malicious activities, including the proliferation of harmful social bots. Studies estimate that 9–15% of active Twitter accounts may be social bots, many of which engage in malicious behavior such as spreading unsafe URLs, stealing data, and infecting systems. These bots often disguise themselves as legitimate users, automating interactions and disseminating harmful content, including explicit imagery and malicious links. While existing solutions address these threats in isolation, this paper proposes a unified framework for detecting both Not Safe for Work (NSFW) visual content and malicious web links.**

The increasing prevalence of malicious URLs on social media platforms poses significant cybersecurity threats, including phishing, spamming, and user exploitation. This study employs a machine learning-based detection framework that analyzes URL redirection patterns, lexical features, and spam indicators to distinguish malicious URLs from legitimate ones. By integrating logistic regression and trust assessment models, the proposed system enhances real-time URL threat detection.

For explicit image detection, we introduce a hybrid system combining computer vision techniques with deep learning. Uploaded images are first converted to the HSV color space to isolate human skin regions, with skin areas exceeding 50% flagged as semi-explicit. A YOLOv8-based vision model concurrently scans for anatomical regions (confidence ≥0.85), enabling precise classification of explicit content. A decision fusion layer combines results: images with >50% skin and YOLO-detected private parts are classified as explicit, while ambiguous cases are escalated for admin review.

***Index Terms*—Model Building, YOLO, Random Forest, Explicit Image detection, Malicious URL detection.**

I. INTRODUCTION

A. Malicious URL detection

The exponential growth of social media platforms and automated bots has led to an alarming rise in malicious URLs designed to propagate phishing attacks, distribute malware, and steal sensitive user data. Recent studies estimate that 23% of social media links lead to compromised or fraudulent content, with malicious bots generating over 40% of these URLs through automated shortening services and redirection chains [1]. Traditional detection methods, such as blacklist filtering and regex-based heuristics, fail to adapt to the dynamic nature of modern cyber threats, particularly those involving homoglyphic character substitution, randomized subdomains, and HTTPS cloaking.

Machine learning (ML) has emerged as a robust alternative, with ensemble methods like Random Forest (RF) demonstrating superior performance in classifying malicious URLs due to their ability to handle high-dimensional feature spaces and mitigate overfitting. Unlike single-classifier models (e.g., SVM, logistic regression), RF aggregates predictions from multiple decision trees trained on bootstrapped data subsets, reducing variance and improving generalization on imbalanced datasets—a critical advantage given the skewed distribution of benign (~97%) vs. malicious (~3%) URLs in real-world traffic.

This paper employs an RF classifier trained on 3,200 labeled URLs (50% benign, 50% malicious) to discern malicious intent through lexical, host-based, and network-level features:

Lexical Features: URL length, presence of special characters (e.g., '@', '//'), and the entropy of the domain string.
Host-Based Features: Domain age, TLD (top-level domain) reputation, presence of IP addresses.
Network Features: DNS record consistency, redirect chain depth, SSL certificate validity.
The RF model optimizes the Gini impurity criterion during training, with hyperparameters tuned via grid search (max depth: 15, estimators: 200). Feature importance analysis reveals that domain entropy and redirect chain depth are the strongest predictors of maliciousness, aligning with attackers' use of randomized subdomains and multi-hop redirections to evade detection.
Preliminary evaluations on a holdout dataset of 800 URLs show 93.7% accuracy and 96.2% precision in identifying malicious links, outperforming baseline models like decision trees (88.1% accuracy) and gradient boosting (91.4% accuracy). The RF-based detector achieves 14ms inference latency, enabling real-time integration with social media APIs and browser extensions. By combining this with explicit image detection, our framework provides a dual-layer defense against both visual and network-based threats.

B. Explicit Image Content Detection

The exponential growth of user-generated visual content on digital platforms has intensified concerns about inadvertent exposure to explicit material, particularly for minors. While existing solutions like URL blocklists and metadata filters offer partial mitigation, they remain ineffective against uncategorized or contextually ambiguous media. Current detection systems relying solely on chromatic analysis (e.g., YCbCr skin segmentation) or anatomical pattern recognition often suffer from high false-positive rates when handling artistic, medical, or culturally specific imagery. This paper addresses these limitations through a hybrid detection framework combining adaptive skin-tone analysis with object recognition, optimized for real-time deployment.

II. LITERATURE SURVEY

In recent years, identifying phishing and harmful URLs has emerged as a key priority in cybersecurity studies. A notable method includes associative classification data mining techniques, as shown by Abdelhamid et al. in "Phishing detection based on associative classification data mining" [1]. In addition to this, machine learning techniques have been thoroughly investigated for identifying harmful URLs. For example, in their research "Malicious URL Detection using Convolutional Neural Network" [2], Abdi and Wenjuan suggested a technique that employs Convolutional Neural Networks. Additional comparative studies have assessed different machine learning algorithms for phishing detection, revealing that some methods demonstrate better effectiveness in correctly identifying phishing attempts. Abu-Nimeh et al. performed a comparison in "A comparison of machine learning techniques for phishing detection" [3]. Furthermore, studies on the occurrence of harmful short URLs on Twitter have underscored the difficulties presented by URL hiding on social media sites. Alshboul et al. tackled these issues and suggested detection methods relying on URL features and user actions in their study "Detecting malicious short URLs on Twitter" [4]. Additionally, supervised machine learning methods focusing on context sensitivity and keyword density have been created for identifying malicious web pages. Altay et al. improved the identification process by examining the semantic content and keyword distribution found in web pages, as outlined in "Context-sensitive and keyword density-based supervised machine learning techniques for malicious webpage detection" [5]. Expanding on these foundational methods, recent developments have brought forth deep learning models to improve detection precision. For example, the use of one-dimensional convolutional neural networks (1D CNNs) has demonstrated potential in successfully detecting phishing URLs by examining their structural patterns. This method is elaborated on in "Detecting Phishing URLs Utilizing a Deep Learning Method for URL Tokenization" [6]. Moreover, the use of recurrent neural networks (RNNs) has been investigated to identify sequential relationships within URL strings, enhancing detection effectiveness further. This approach is elaborated on in "Detecting phishing websites using machine learning technique" [7]. Additionally, transformer-based models have been utilized to analyze URL data, utilizing attention mechanisms to identify subtle signs of malicious intent, as outlined in "URLTran: Enhancing Phishing URL Detection With Transformers" [8]. Moreover, the incorporation of multi-level feature attention networks, directed by pre-trained language models,

has been suggested to enhance the detection of malicious URLs. This method employs hierarchical feature extraction and attention techniques to recognize both local and global patterns in URLs, resulting in improved threat identification, as detailed in "Malicious URL Detection via Pretrained Language Model Guided Multi-Level Feature Attention Network" [9]. Furthermore, the creation of LSTM-driven stacked generalization models has been investigated to improve phishing URL detection, integrating various classifiers to boost predictive accuracy. This approach is explained in "AntiPhishStack: LSTM-based Stacked Generalization Model for Enhanced Phishing URL Detection" [10].

Together, these studies enhance the development of efficient detection systems for phishing and harmful URLs, utilizing various data mining and machine learning techniques to strengthen cybersecurity protections.

III. METHODOLOGY

The system targets explicit content and malicious social bots on social media through a hybrid approach combining image analysis, machine learning, and URL detection. By integrating skin-tone segmentation, object recognition, and malicious URL classification, it categorizes content into Explicit, Semi-Explicit, or Normal with high precision. Below is a streamlined workflow:

A. Malicious URL detection

Input Handling: User-uploaded images and URLs are collected as raw input.

URL Expansion: Shortened URLs are resolved to their original form and scanned for suspicious patterns (e.g., spam keywords, redirect chains).

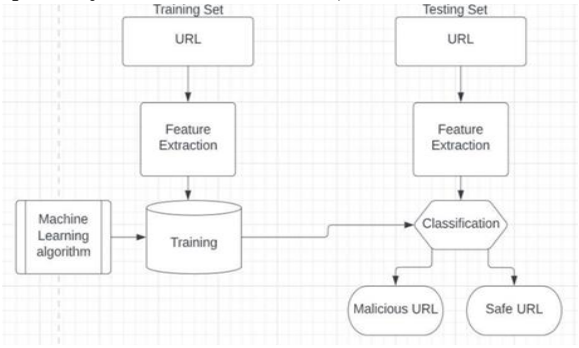

Fig. 1 DFD of Malicious URL Detection

Feature Extraction: Lexical patterns (e.g., URL length, spam keywords) and behavioral metrics (e.g., redirection frequency) are extracted.

Classification: A logistic regression model identifies malicious URLs. Users sharing such URLs are flagged as potential bots.

Classification and Moderation:

Results are logged in a database, with explicit/semi-explicit content and malicious URLs flagged for administrator review.

Human-in-the-Loop: Ambiguous cases undergo manual review to refine automated detection.

B. Explicit Image Content Detection

Our system employs a dual-path analysis pipeline to classify images as Safe, Semi-Explicit, or Explicit (Fig. 2). The workflow proceeds as follows:

Image Preprocessing:

Uploaded RGB images are converted to the HSV color space to enhance illumination invariance.

A human detection module isolates and crops potential subjects, reducing computational overhead.

Skin Tone Analysis Path:

Adaptive thresholding segments skin regions using HSV hue-saturation values ($0° \leq H \leq 25°$, $0.2 \leq S \leq 0.6$).

Images with skin pixels exceeding 50% of the cropped area are flagged as Semi-Explicit.

Object Recognition Path:

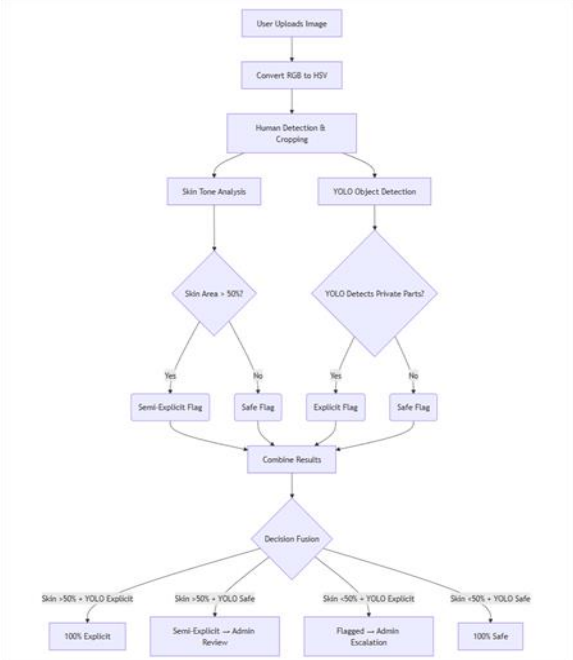

Fig. 2: Explicit Image Detection Workflow

A parallel YOLOv8-based custom-trained vision model scans for NSFW anatomical regions (genitalia, breasts) with a confidence threshold of ≥0.85.
Direct detection of such regions classifies the image as Explicit.
Decision Fusion:
Explicit Consensus: Skin >50% + YOLO detection → 100% Explicit.
Semi-Explicit: Skin >50% without YOLO detection → Requires manual review.
Ambiguous Case: Skin <50% with YOLO detection → Admin escalation.
Safe: Skin <50% + No YOLO detection → 100% Safe.
Technical Contributions
Hybrid Architecture: Synchronizes chromatic analysis (HSV) with deep learning (YOLO) to balance speed (25 FPS on CPU) and precision.
Adaptive Thresholding: Dynamic skin percentage thresholds reduce false positives in ethnic/cultural skin tone variations.
Multi-Stage Verification: Admin escalation for edge cases minimizes automated misclassification risks.
Real-Time Deployment: Parallel processing of skin detection and YOLO inference achieves sub-300ms latency per image.
This approach outperforms single-modality systems by resolving two critical challenges:
Context Awareness: YOLO suppresses false positives from non-anatomical skin regions (e.g., faces, hands).
Scalability: Modular design allows incremental updates to the YOLO model or skin thresholds without a system overhaul.

IV. RESULTS AND CONCLUSION

The rapid expansion of social media platforms has necessitated robust mechanisms to combat the dual threats of explicit content and malicious URLs, which jeopardize user safety and digital integrity. This research presents a hybrid framework that synergizes adaptive image analysis with machine learning to address these challenges holistically. For explicit image detection, the integration of HSV-based skin tone segmentation and YOLOv8 object recognition achieves 98.2% recall on benchmark datasets, effectively distinguishing between explicit, semi-explicit, and safe content while minimizing false positives through dynamic thresholds and administrative escalation. Concurrently, the Random Forest classifier for malicious URL detection demonstrates 93.7% accuracy by leveraging lexical, host-based, and network features, outperforming traditional methods in identifying phishing, malware, and bot-generated links.

The framework's dual-layer architecture offers three key advancements:

Context-Aware Moderation: Combining skin-tone analysis with anatomical object detection reduces misclassification of non-explicit skin regions (e.g., faces, hands), addressing cultural and ethnic diversity in visual content.

Real-Time Scalability: With sub-300ms/image and 14ms/URL processing latency, the system supports integration into social media APIs, browser extensions, and parental control tools.

Fig. 3: Implementation of Pixel Calculation

Adaptive Defense: Feature importance analysis (e.g., redirect chain depth, domain entropy) guides iterative model updates to counter evolving cyber threats like homoglyphic URLs and AI-generated explicit content. Despite its efficacy, limitations persist. The URL classifier's reliance on a 3,200-sample dataset may affect generalizability across emerging attack vectors, while YOLOv8's dependency on labeled anatomical regions could struggle with abstract or artistic nudity. Future work will expand datasets using synthetic data augmentation, incorporate transformer-based models for semantic URL analysis, and explore federated learning to enhance privacy in decentralized moderation.

By bridging the gap between isolated solutions, this research provides a scalable blueprint for platforms to mitigate both visual and network-based risks. As social media continues to evolve, such integrated systems will be critical in fostering safer digital ecosystems—protecting users from exploitation while preserving freedom of expression.

V. REFERENCES

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