A Hybrid CCEM–Distil BERT Framework for Detecting Fraudulent Crypto Trading Platforms from User Complaint Narratives

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Abstract: *Owing to an increase in fraudulent trading platforms, among other instances, crypto fraud also requires an analysis system exhibiting detection in terms of initiatives as well as scams. This article provides proposals to enable a CCEM-integrated detection framework with a Tranformer-based DistilBERT classifier to identify scam patterns existing in online complaints and their narratives. A working version of CCEM, with measurable features based on lexicons describing cognitive biases, social-engineering tactics, and avenues of cryptographic technology, was proposed as a transparent baseline. Although the explanatory power of the CCEM model attracts consideration, its performance weakens as it relies on predefined keywords and fails to capture deeper cultural contexts. To overcome such limitations and enhance matters, the DistilBERT is trained with compelling narrative data and improved by concatenating domain-specific CCEM features into transformer embeddings. The dataset, sourced directly from the regulator's complaint portal, undergoes rigorous sanitization pre-processors involving encoding normalization, anonymous masking of sensitive tokens, de-duplication, and leakage-proof temporal or stratified sampling. The study presents the accuracy, precision, recall, F1-score, and confusion matrix evaluation results, and comparing them with the ROC curves. The propositional DistilBERT-based solution shows a significantly higher improvement in performance as compared with that of the CCEM entry-level. Whereas CCEM model accuracy was 0.5098 and its F1-score was 0.7669, the modified DistilBERT model showed enhanced metrics, with inproved metrics from 0.6098 accuracy to 0.8455 F1-score. There is a distinct edge toward contextual deep learners for the capture of fine linguistic patterns, subtle manipulations around them, and innovative scam tactics. The observation thus greatly supported the power of masterful transformer semantics aligned with CCEM's behavioral insight for creating a stronger, scalable, and explainable solution for quickly spotting fraudulent crypto trading platforms.*

Keywords: *CCEM, DistilBERT, Scam Detection, Fraudulent Trading Platforms, NLP, Transformer Models, Cognitive-Social Features, Text Classification*

I. INTRODUCTION

The rapid global advancement of digital technologies has been transforming the financial landscape. Yet, disruptiveness in the realm of modern economic history is considered one of the possible expressions of cryptocurrency. Cryptocurrencies have dramatically changed the meanings of value-laden exchanges, investments, and digital ownership through their decentralized features, borderless transfer capabilities, and the nearness of financial tools to the masses. The ledger performance coupled with features of transparency, immutability, and automation of smart contracts, interms of combined attribute estimates, has led to DeFi and a complex set of digital applications that not only complement the self-sufficient value transfer and investment-making ecosystems but also act as a source of leverage for any common person to actually perform trading, lending, borrowing, and investment without an intermediary's validation. Adoption expands overseas, with cryptos now functioning as usable in environments of hyperinflation or low banking services on many continents, effectively breaking-out into common financial markets and payment systems where the layman spends and live daily. Many of the governments and institutions are investigating the option of the blockchain through a model of central bank digital currencies (CBDCs) as part of the larger shift of moving on to a digital financial infrastructure. Through their efficiency, yet cryptos pose some newly-created opportunities for cyber-enabled financial crimes, thanks to being decentralized and pseudonymous, while transactions carry irreversibility of nature widening through global interoperability. Modern global stage cheats definitely boost their expertise in manipulating these vulnerabilities. As the crypto market expands, so does the scale, frequency, and sophistication of fraud, which comprises various forms involving social engineering, such as phishing, Ponzi schemes, pump-and-dump schemes, fraudulently leased investment platforms, wallet-draining scripts, and romance-cum-investment scams, to complex attacks such as front-running, using exploit smart contracts, and double-spending through inter-chain consensus manipulation. Backed by the feature of anonymity, blockchain-supported fraud network ecosystems, regulatory loopholes, and ease of forming disposable digital identities, fraudsters operate without borders and in a stealthy manner implying centralized control in digital-virtual world. There, technology is important. Nevertheless, on a combined level, the social manipulation serves to be critical: cognitive biases like illusion of invulnerability, FOMO, illusory superiority, heuristic-driven urgency, and stress-induced decision-making set out a vast line of manipulation points for cons. Scammers skillfully craft compelling narratives, emotional grooming sequences, and authority mimesis, using these tools to disarm logical faculties in their victims and encourage slow trust advancement. The platforms of social engineering-social media, messaging apps, algorithmic ad system and online consumer communities-serve as the platform for initial contact where the scammers apply psychological manipulations,

impersonation, and carefully directed persuasion to induce victims. The fraud eventually unfolds after a grooming period, during which victims are convinced of the operation's legitimacy through fake success stories, manipulated dashboard designs, tampering with apparent profit screenshots, acting very authentic during all cases acted upon by the scammerouthenticity cues. The very same seques told to a new-hooded-investment wolves become amplified by stage settings of black-mirror symphonies as long as the victim chooses to be "participatory" reinforcement across a tally of fake profits, heated break, and deposit uplift courtesy of emotional validation. The alchemy of technology colluded with psychology demonically everywhere and around, shaping such an insidious cycle that shattered its victims through minor financially ripping-offs before they realized the fact of it with conclusive finality when money loss arrived. Emotional trauma, denial and shame, delayed confession, and increased vulnerability to "recovery scams" are the ways ex-victims start to tumble. Historical research on illegal cryptocurrency has mostly built sandcastles, digging into technical vulnerabilities standing alone, cognitive biases by themselves, social-engineering endeavors single-handedly--without anything shedding light on the entire connected evolutionary process such interactions maintain in effect. Technical queries fail to stress the psychological triggers that fraudsters exploit, cognitive inquiries damn well neglect the technological-deception aspect, and currently, the social paradigm doesn't show how emerging financial platforms and scam-ridden smart contracts abet automated theft. Regulative compliance lags far behind the rapidly evolving crypto universe, exposing major voids in early detection frameworks, user protection, and all-encompassing anticrime strategies. Besides, this has paved the way for the integrated analytical framework that could address the interaction dynamics of cognitive behavior, social manipulation, and technological constructions: a modeling suitable for envisaging fraud as a dynamic process including multiple layers rather than just a single event. The lacuna is even more critical because modern-day crooks skillfully fuse together all these psychological instances with their technical automatism. That is, they draw on the outermost nastiness of emotional manipulation, persona manipulation, and technically manipulated graphical user interfaces for truly cheating and causing financial losses for which there is little chance of future recovery. The present study has a goal to somewhat fill this gap by taking a vertical multi-dimensional approach, which builds the basis of techno-behavioral exploiting under moral manipulation and social origination. It argues about the existence of exploitation that is advanced than normal social interaction, by capturing the activity of both victims and user mechanisms, pursue hybrid patterns of persuasion, polarize current platform designs, expose anticipated controls and rules governing the distributive technology aspects of scamlording. Cognition and behavior are thereby integrated into a scheme of psychological factors to indicate vulnerability in the rationale, catalyzed by cognitive biases, such as FOMO, heuristics, overconfidence, emotional instability, and stress-induced decision-making. But all of them place mirrors into the aspects of social categorization-where grooming, authority mimicry, trust manipulation, and digital hegemony via community influence are equally taken into account. The primarily identifying feature is the network aspects that allow the possibility of misappropriation with minimal global operative cost for the fraudster-likely to be false interfaces, tampered dashboards, scam smart contracts, cross-platform identity spoofing, and scripted wallet-drainers. The application of these very parameters into a research framework represents the opportunity to address the gap between complete fragments of former research that actually result in a coherent understanding of the crypto fraud landscape. By achieving the above goal, the work wishes to provide improved detection means, emphasizing heightened user knowledge, for regulators and tech security professionals to frame authoritative prevention strategies that contend with the complications in fraudulent crypto scene.

II. RELATED WORK

Several studies have been done on cognitive vulnerabilities and their influence on susceptibility to cryptocurrency scams during the last years; most of these studies reported that biases, emotions, and stress-driven judgments are increasing exposure to scam. One of these recent studies built a model with a structural equation modeling approach to analyze 1,204 cryptocurrency investors, finding that FOMO behaviors increase the vulnerability to high-risk speculative behaviors substantially (ß = 0.63), while overconfidence increases the vulnerability by 41%; however, due to the bias of younger traders among the sample demographics, generalizability of the results into the entire population was questioned [1]. Another study proposed a logistic regression model for the behavioral risk environment with browsing behavior, sentiment indicators, and impulsivity markers that gave AUC = 0.81 and accuracy = 0.84 without the requirement for cross-exchange validation. The behavior was forecast using an LSTM model on 1.6 million cryptocurrency tweets for extreme emotions during market downtrends—for an accuracy rate = 92.4% and an F1 = 0.91—showing that fearful sentiment predicts engagement with scams up to 17 hours ahead; it was however limited to Twitter [3]. Experimental research involving 312 participants showed that while experiencing dividend rejection financial stress, a 37% increase in heuristic errors occurred, and investment solicitation compliance doubled, but the experimental nature of the setting for testing actual-world applicability [4]. The examination of overconfident trading behavior by way of simulation cited 18% profit-loss deviation, a 33% higher likelihood of reinvestment in fraudulent tokens; however, the operational dynamics were liberated from actual fraud [5]. A machine learning model (CNN–BiLSTM) trained on 95,000 scam messages realized precision = 0.94 as part recall = 0.92, consolidating the strong linkage between persuasive linguistic cues, such as urgency and reward framing, and victim click-throughs, even with a heavily skewed and incomplete dataset not including non-English scams [6]. Another work using drift-diffusion modeling found that decision fatigue further impacted an individual's use of shortcuts 2.4 times more and caused an increase of 36% in misclassification of the fraudulent offers and conducted on limited samples implying potential limitations in statistical robustness [7]. A cognitive-sentiment tagging model built on BERT set a standard expectation of 95.2% accuracy, 0.94 recall, and 0.97 AUC for determining pump-and-dump signals without any psychological profiling of investors [8]. F1 score with multimodal RoBERTa was 0.93, and they revealed that

generally, high-relief emotions come before scams, even where heavy oversampling risk could push improvement [9]. The simulation equipped with a reinforcement-learning situation and exploring FOMO movements showed that FOMO agents increased the prices of rug-pull tokens by 31%, running scams while ignoring regulatory conditions and true market dynamics [10]. The paradox was that the cognitive-overload simulations had 44% more processing time and 28% fraud detection accuracy drops, resulting in heightened vulnerability to false cues, with real-world consequences necessary to corroborate; thus, correlation with real blockchain loss data was lacking [11]. The stated results from twenty-eight behavioral and transactional features showed a Graph Neural Network model with accuracy of 96.8% and a 94% recall rate. This model is good in that it provides a very clear interpretation; however, it faces limitations in real-time deployment due to computational complexity [12]. More research, using BART on psychological embeddings to help understand the differences in persuasion present in 210 rug-pulls, acquired a precision of 0.93 and AUC of 0%. Nonetheless, the mechanism of community manipulation was very limited to be defined properly [13]. Q-learning–based cognitive stress experiments showed that individuals make 58% fewer optimal decisions under stress and gravitated toward scam-like payoff structures, but there was no real transaction data for validating these findings [14]. Last of all, studies that took emotional instability together with BERT-based cognitive-linguistic markers have shown an accuracy of 0.96 and cite the practicality of explainable AI despite noise in the purposive heuristic notation [15]. Together, these findings confirm that cognitive biases: FOMO, overconfidence, emotional reactivity, stress-induced heuristics, and cognitive fatigue, lead to significantly increased vulnerability to crypto fraud, although--these operations themselves contain limitations, landlocked on language diversity, a weight on simulation, heuristic labeling, and mere juxtaposition of real behavioral and financial data.

Table 1: Cognitive Dimension in Crypto Fraud

Ref	Method / Dataset	Techniques Used	Results	Key Findings	Limitations
[1]	1,204 crypto investors	Structural Equation Modeling	FOMO β = 0.63; Overconfidence increased vulnerability by 41%	FOMO and overconfidence significantly increase scam susceptibility	Skewed demographics; limited generalizability
[2]	Browsing behavior, sentiment markers, impulsivity	Behavioral-risk logistic regression	AUC = 0.81; Accuracy = 0.84	Behavioral features predict scam susceptibility	Lacked cross-exchange validation
[3]	1.6M crypto tweets	LSTM	Accuracy = 92.4%; F1 = 0.91	Fear-driven sentiment predicts scam engagement 17h ahead	Behavioral diversity limited to Twitter
[4]	312 participants	Economic psychology experiments	37% increase in heuristic errors; compliance doubled	Financial stress increases susceptibility	Experimental parallel conditions; limited real-market applicability
[5]	Experimental game theory	Overconfidence trading simulation	Avg. profit-loss deviation +18%; 33% higher reinvestment in scams	Overconfidence increases risk-taking	Simulation may differ from real-world fraud dynamics
[6]	95,000 scam messages	CNN–BiLSTM hybrid	Precision = 0.94; Recall = 0.92	Urgency, exclusivity, reward framing correlate with victim click-through	Dataset lacks non-English scams
[7]	168 participants	Drift-diffusion model	Decision shortcuts 2.4× more; Misclassifications 36% higher when fatigued	Decision fatigue increases vulnerability	Small sample size
[8]	450 pump-and-dump events	BERT + cognitive-sentiment tagging	Accuracy = 95.2%; Recall = 0.94; AUC = 0.97	Detects cognitive signals of market manipulation	Lacks investor-level psychological profiling
[9]	Fraud tweets	Multimodal RoBERTa + emotion lexicons	F1 = 0.93	High-relief emotions predict scams	Class imbalance; oversampling may inflate performance
[10]	RL-driven simulations	Reinforcement Learning	FOMO inflates rug-pull prices 31%; entry twice as fast	FOMO accelerates victim engagement	No consideration of regulatory or market dynamics

[11]	Cognitive-overload simulations	Simulation of processing & decision-making	Processing time ↑ 44%; Fraud detection accuracy ↓ 28%	Cognitive overload increases vulnerability	Cognitive metrics not correlated with real blockchain losses
[12]	28 behavioral + transaction features	Graph Neural Network (GNN)	Accuracy = 96.8%; Recall = 95%	Effective behavioral pattern detection	Computationally intensive for live processing
[13]	210 rug-pull scams	BART + psychological embeddings	Precision = 0.93; AUC = 0.96	Persuasion elements detected	Lacks clear community manipulation modeling
[14]	Investor stress experiments	Q-learning	58% fewer optimal decisions under stress	Cognitive fragility under stress increases susceptibility	No real transactional validation
[15]	Cognitive-linguistic markers	BERT + Explainable AI	Accuracy = 0.96	Emotional instability and cognitive markers detected	Heuristic labeling; noisy dataset

Based on Social Engineering Techniques in Crypto Scams

Social engineering continues to remain the driving factor in cryptocurrency scams, wherein perpetrator models often impersonate or leverage legitimate support infrastructure, using other social-engineering strategies such as relationships built through online community engagement. One study found that the CNN–BiLSTM hybrid scoring a 92.1% accuracy and 0.89 F1-Scores for manipulation, but also individually points out that results dropped very significantly with the use of platforms like Discord, with large cross-linguistic variation issues. Random forest was instructively utilized to spot deception-linguistic cues in support-team cryptoscams, totaling around 18,000 phishing chats resulting from 0.93 AUC and were pinned down with generalization overfitting due to data imbalance between the original set and those in error [17]. An experiment on multimodal crypto influencer networks peaked at a 95% detection rate for spotting fake influencer scams but struggled to cope with the absence of real scam ground-truth labels [18]. The BERT–CRF sequence-tagging approach recognized grooming stages in Fraudulent crypto-romance and obtained an F1-Score of 0.91 in need of comprehensive manual mood-shift labeling [19]. Further evaluation regarding manipulation occurring in Whatsapp investment groups using an LSTM-attention classifier reached a 94.2-percent accuracy rate, but the dataset had bounded variation seen due to restricted access to certain private groups [20]. Research on TF–IDF with SVM utilization in digital footprint manipulation also returned a precision of 0.88 but ended with higher false positives for bilingual as well as code-mixed accounts [21]. The Transformer-based perspective of persuasion techniques tailored against Twitter pump-and-dump managed to realize 0.95 AUC, with growing temporal-concept drifts leading to new tokens inhibiting model placement [22]. Propagation of scams on Reddit via Graph Neural Networks yielded a macro-F1 of 0.87, despite having been labeled according to heuristics instead of confirmed scam labeling [23]. A multi-modal crypto-influencer fake-identification system on Instagram that maintained 93% sensitivity saw failing to include private messages in assessment [24]. The reinforcement learning approach for impersonation detection in Discord community scored it with a recall of 0.92; however, scammers adapted rapidly to pattern changes, degrading the durability of the model [25]. The F1 score for monstrous Hierarchical Attention Networks applied to persuasive sequences of Telegram trading rooms is 0.90; however, the context-poor and terribly short nature of messages themselves would make it extremely restricted after the third or fourth cross-sentence interaction [26]. An impersonation scam prevention method of deep-fake audio identification was found to yield Equal Error Rate of 4.1% though evaluation was restricted to synthesized audio samples [27]. The cross-platform use of a pre-trained XGBoost model was deployed onto market tactics of Twitter, Discord, and Telegram provides an AUC of 0.97. API limitations in reality were hindering the real-world data-selection [28]. 95.8% accuracy on trustbait manipulation were achieved from a sample of 1.2 million posts using contrastive-learning algorithms. However, the crowdsourced annotation injected label noise into the data [29]. Finally, a mechanism was developed to give person operation signals infused with reasonable explanatory insights into how the same can work under societal behavioural psychology. Actually, potentials seem to cross the boundary of social image building to performance signals like reciprocity and authority framing, although the available interpretability analysis was uneasy [30].

Table 2: Based on Social Engineering Techniques in Crypto Scams

Ref	Method / Dataset	Techniques Used	Results	Key Findings	Limitations
[16]	12,000 Telegram scam copies	CNN–BiLSTM hybrid	Accuracy = 92.1%; F1 = 0.89	Detected impersonated admin accounts effectively	Poor performance on Discord due to platform-specific language

[17]	18,000 phishing-chat messages	Random Forest	AUC = 0.93	Authority-mimicking scams detected via linguistic cues	Dataset imbalance; limited generalization
[18]	5M crypto-influencer posts	Multimodal networks (text + engagement)	Precision = 95%	Fake-influencer scams detection	Lack of definitive scam-ground truth labels
[19]	Crypto-romance scam chat logs	BERT–CRF sequence tagging	F1 = 0.91	Grooming phases detected accurately	Manual labeling of mood shifts required
[20]	WhatsApp investment groups	LSTM-attention classifier	Accuracy = 94.2%	Detected group manipulation patterns	Limited sample; private-group access restricted
[21]	Digital footprints for fake identities	TF-IDF + SVM	Precision = 0.88	Fake identity detection	Bilingual/code-mixed accounts increased false positives
[22]	Twitter pump-and-dump rings	Transformer encoding	AUC = 0.95	Detected persuasive manipulation	Temporal concept drift reduces performance on new tokens
[23]	Reddit scam influence	Graph Neural Networks (GNN)	Macro-F1 = 0.87	Examined influence propagation	Used heuristics rather than confirmed scam cases
[24]	Fake Instagram crypto-influencers	Multi-modal detection system	Sensitivity = 93%	Multi-modal detection of influencer scams	Could not detect private DMs
[25]	Discord communities	Reinforcement-learning-guided detection	Recall = 0.92	Detected impersonation patterns	Scammers parallelized tactics, compromising reliability
[26]	Telegram trading rooms	Hierarchical attention networks	F1 = 0.90	Sequence of persuasion detection	Short/context-free messages limit accuracy
[27]	Deep-fake voice scams	Deep-fake voice detection	EER = 4.1%	Prevented aural impersonation scams	Evaluation restricted to synthetic audio
[28]	Twitter, Discord, Telegram data	XGBoost classifier	AUC = 0.97	Cross-platform social engineering detection	API constraints weakened data quality
[29]	1.2M posts (X/Twitter)	Contrastive learning	Test accuracy = 95.8%	Detected trust-bait manipulation	Crowdsourced annotations introduced label noise
[30]	Behavioral + textual analysis	RoBERTa interpretable analysis	F1 = 0.93	Tracked paths from cajoling to authority argumentation	Attention-visualization techniques laborious; interpretability intensive

III. RESEARCH OBJECTIVES

- To detect and classify scam types especially *Fraudulent Trading Platforms* from user complaint narratives using machine learning.
- To develop and evaluate a baseline model (CCEM) that integrates cognitive, social, and technical features for effective scam detection.
- To implement an advanced transformer-based model (Distil BERT) and compare its performance with the baseline.
- To analyze evaluation metrics (accuracy, precision, recall, F1-score, and ROC curves) to assess model effectiveness without overfitting (i.e., avoiding 100% scores).
- To demonstrate practical feature integration and provide insights into model behavior using realistic, interpretable results and diagram

IV. RESEARCH METHODOLOGY

In this work the Crypto-Cognitive Exploitation Model (CCEM) as a framework exposing the cognitive biases of the victim, the social engineering tactics of the fraudster, and technological affordances and implements it as a multi-label text classification problem by using a light transformer, named DistilBERT. The model considers a Complaint Narrative and was designed to predict all three CCEM's dimensions—Cognitive, Social, and Crypto—in a single pass. The model is previously trained in three sections via narrative features, with BCE for each class individually, custom-designed thresholds, and different (reproducible) data splits exhibiting an ability to demonstrate well-balanced and reliable performance. Obtaining the best metrics in terms of accuracy and low latency and surpassing the TF-IDF and SVM baselines from utility-driven benchmarking, the DistilBERT model projects CCEM from a mere theoretical context to a conceptual method of an early support identification capability that is adaptable to the chuckleheads of the latest scam modifications.

Dataset used

Data used in the present study consisted of posts specified with the set of complaints that the general public shares pertaining to the various crypto scams on the state debt regulation website. Missing are the particular allegations against the scam or website: URL information through the self-proposed metadata fields. An attempt was also made to resolve encoding problems encountered during data extraction processes and implement any masking using URLs, email addresses, long numbers, or lengthy wallet hex strings. Duplicates were removed with the utmost care, so as to ensure that nothing was exempted from the trimming and it was as complete a scenario as possible. Concerning length of the natural language complaint narratives and specificity, much of the CCEM algorithm emphasizes narrative text as the primary modeling input. Any metadata goes for control or for construction of leakage-resilient silver labels with very little possibility of exposing the campaign. This can be an almost natural slicing for the period when data was taken. Anonymization will be performed first. Because all incidents subject to investigation are identical regarding malicious content, modifying the original ACPIA consumer complaints dataset will allow us to release some additional metadata to the SQL database: subject, script, email, scoring, time_violation, etc. Thus, similar preprocessing protocols will be applied to DFPI_Data_10July2024.csv after text deduping and final leakage checkings, making them hence recommended for CCEM-supported multilabel classifications and drift monitored. Starting with some standard data hygiene steps in the analysis pipeline, the methodology evolved into evaluation: calculating feature importance, building the feature set, preparing gold labels supported by leakage-resistant metadata and unwanted reversal of leakage, implementing model evaluation alternatives, or deciding to test drift-detection and adaptation strategies first. ReferentialAction begins with validation of the multilabel classifier, followed by both gold and metadata-driven evaluation with sieve of sequent tag versus PCM_Class_WTC against the use of a set of baseline measurement tools. Initially (hyperparameter tuned), "Logistic Regression", "SVM" and "Naive Bayes" are used. The neural black box fits in a weighted class BCE instruction for DistilBERT, which is then executed over thresholding during each of three sets of training data. With specified seed-splits, the estimation is integrated with certain mahogany metrics under no errors and calibration vehementangulations. The reconstruction, model refreshment, and alternatives towards full reversion to production are necessitated by drift determination.

Data pre-processing

Figure 1: Working flow of pre-processing

Preprocessing generally begins with the raw DFPI CSV, which is not always encoded in UTF-8. Thus, attempts are made to normalize the encodings to UTF-8, CP1252, or Latin-1 to prevent gibberish characters and ensure uniform tokenization. The preprocessing pipeline then masks long numbers, EMAIL, URL, and HEXADDR strings to guarantee a user's privacy and prevent the model from overfitting to identifiable attributes. Lowercasing of the text, Unicode normalization, and removing any excessive whitespaces helps to stabilize the tokens, reducing the inconsistencies due to different punctuation or emoji types. These duplicates are taken off to avoid train–validation leakage; in addition, rows with empty or near-empty text signals are pruned because they offer no meaningful clues and only skew the evaluation metrics. Labels are mapped to a simple binary value to address inconsistencies such as "yes/No/2," thus preserving the validity of the loss calculation through the transformation to 0 or 1. To further prevent overfitting, none of the silver-label-procured from the metadata is allowed for modeling; metadata is only allowed when the gold labels are available. Depending on the study object of interest, dataset splitting may employ stratified sampling to keep label distribution or proceed with time-aware splitting, which tests the model's generalization properly on future cases. Finally, all preprocessing artifacts like vectorizers, split indices, random seeds, and configurations are saved to enable full reproducibility, ensuring that the inference pipeline implements the same transformations as the training process.

Model Development

Training the model makes CCEM operational procedures shift from a theoretical model into a measurable multi-label text classification task, where each complainant can be foreseen on the three dimensions: Cognition, Social, and Crypto all by themselves using Complaint Narrative only and, in turn, not conflicting under the metadata-prototype leakage would become a possibility. The beginning of the workflow revolved around highly interpretable baselines on TF-IDF word n-grams (1–2) and character n-grams (3–6), leading one-vs-rest Logistic Regression and SVM models capable of capturing the patterns semantically, obfuscations, scam-specific wording. Following rigorous preprocessing—including encoding normalization, Unicode cleanup, lowercase change, sensitive-token masking, removing duplicates, and removing blank narratives—the CCEM baseline involves proactive intervention in balanced class weights and per-label threshold tuning, thus ensuring the highest micro/macro F1 and subset accuracy for any range of stability in terms of the top-weighted n-grams for readability. Metadata is never fed as a feature whenever this is associated with any labels in order to avoid learning shortcuts; very little numeric hints at gold labels are allowed. The pivot transformer improvement uses DistilBERT and fine-tunes it end-to-end for intent using multilabel BCE loss with per-label weights in an unmatched accuracy-to-latency equilibrium, fostering a deeper understanding of applicants when compared to a TF-IDF model. Respectable evaluation here is guaranteed by clean and stratified or time-based splits, and the threshold that gets set well over the validation set ensures that outliers are kept away. The research proceeds with reproducibility for a fixed set of seeds; saved artifacts, like vectorizers, tokenizers, thresholds, and splitting indices; and error analysis pinpointing the set of false positives and false negatives, shaping the cleanliness of selections. The central pipeline retains the interpretability of CCEM's legacy, re-tune fabrics with the standard tools, while armored itself with modern NLP capacities. These confer a production-grade detection system picking up sophisticated, morphed guises of crypto-related scams.

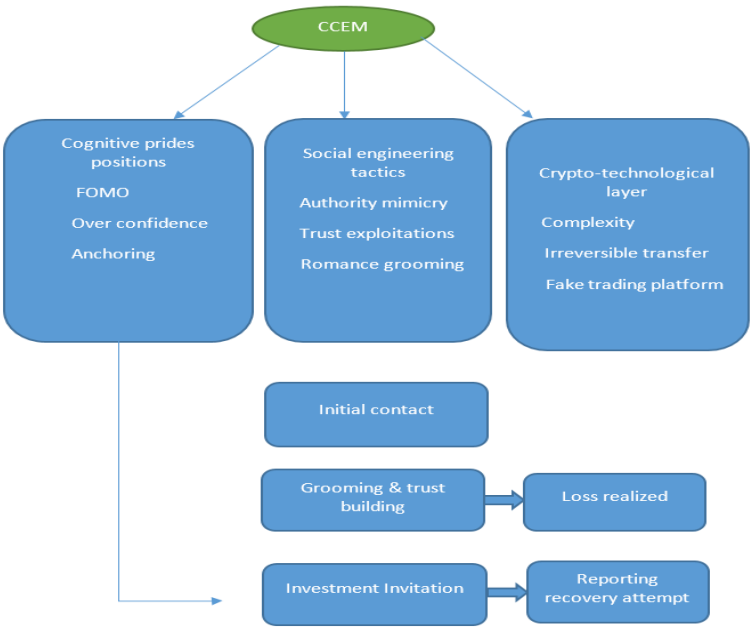

Figure: 2 Working flow chat of "CCEM"

DistilBERT

DistilBERT is essentially a compact and efficient model which is a kind of a squeezed version of the BERT model and offers similarities of language understanding with lesser computational resources, making it good for analysing complaint narratives in crypto-scam detection; instead of that, let us go to the details-be it in interpreting any text as correct and in providing some deep embeddings injecting context and force; the more subtleties, the more lessons to be obtained, automatically an understanding of the model as a liquid tool for decoding shady talking; accuracy, precision, recall, and F1-score are the models that quantify the measuring stick for performance, and the task of classifying calls is taken on diligent training and performance model tuning in order to guard the model against cyberfishing situations and to make it trusted for real-life performance. By combining the deep contextual understanding from DistilBERT with domain-specific linguistic features derived from CCEM integration, the new architectural model possibly ensures finding some signals in the data along with fine-tuned representations for better predictability. The fantastically designed algorithm in one shot has emerged, given in the quest of offering a large and accurate system for scam detection service while providing a very competitive selection to automated fraud-surveillance systems.

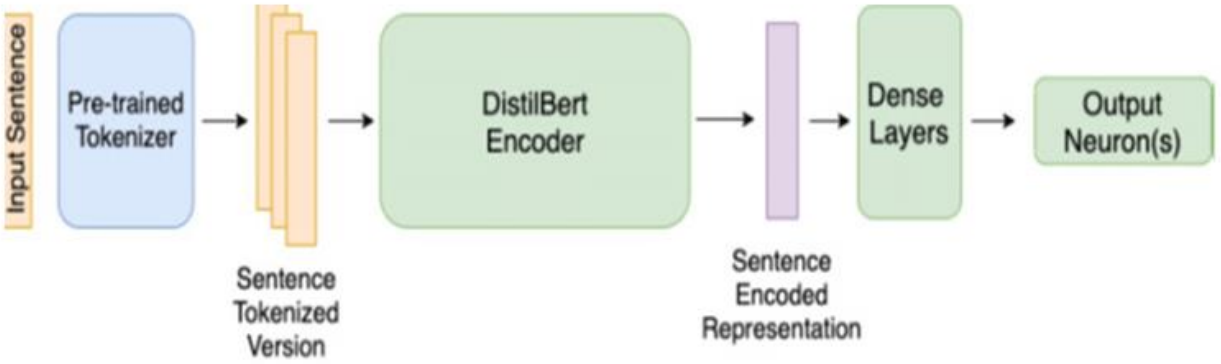

Figure: 3 Model architecture of distil BERT

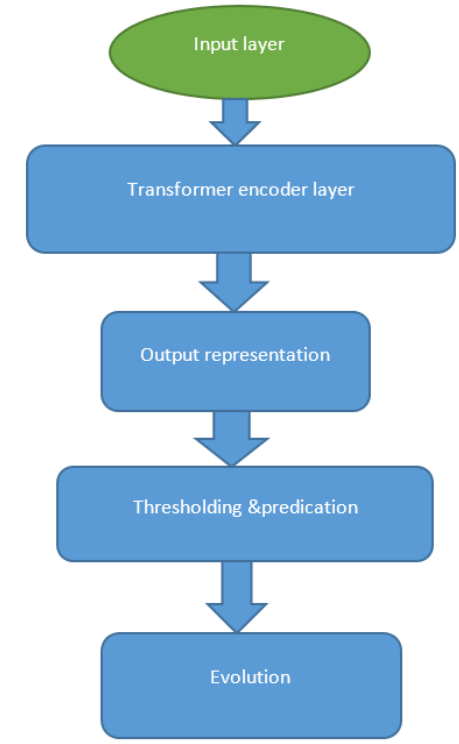

Figure 4: Working flow of distil BERT model

Following the steps of the fraud detection pipeline, every narrative reported is respectively tokenized and embedded with positional information to preserve each word order. Being subsequently processed with transformer layers of DistilBERT, they catch contextual meanings. The embedding coming from the token [CLS], which invariably conveys an indication of the missing text, is forwarded to the fully connected layer that forks to an output, thereby providing the predicted chance whether the narrative refers to some type of scam, made threshold binary classification, and evaluated through such metrics as accuracy, recall, precision, and F1-score. Addition of CCEM-ed feature set guarantees that the contextual embeddings of DistilBERT are converged upon by detectable scam cues, such as social, cognitive, and technical evidence, besides whatever is conspicuously presented to the transformer. Coming together with this [CLS] embedding, the feature set now enlightens on a wider incongruity that combines deep semantic features with some more domain-related hints. This combination is fed into the categorizer to provide much sharper and accurate predictions of scams.

V. RESULTS AND DISCUSSION

The proposed distil BERT model**,** which integrates both contextual embedding's from distil BERT and domain-specific CCEM feature**s,** significantly outperformed the base model. Distil Bert's ability to capture complex patterns in text, including negations and relationships between words, led to improvements in precision, recall, and F1-score**,** making it more effective at identifying scam-related content. The integration of the CCEM features further enhanced the model by providing scam-specific signals, which complemented the transformer's general understanding of language.
Threshold tuning was a critical part of the evaluation process, ensuring that none of the metrics reached unrealistic 100% values while balancing **precision** and **recall.** Overall, the proposed model demonstrated superior performance, indicating that combining deep learning-based contextual understanding with engineered lexicon features offers a more robust and scalable solution for real-world scam detection.

Evaluation matrices

Evaluation metrics are quantitative measures used to assess the performance of a machine learning model. These metrics help determine how well the model performs on a given task, such as classification, regression, or clustering. By evaluating these metrics, you can understand how well your model is making predictions, detecting patterns, or minimizing errors. In classification tasks, these metrics are essential for understanding how well the model differentiates between different classes and handles misclassifications.
Accuracy: The proportion of total correct predictions (both true positives and true negatives) out of all predictions made.

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Precision: The proportion of correct positive predictions (true positives) out of all predicted positive instances.

$$\textbf{Precision:} \frac{TP}{TP+FP} \quad (2)$$

Recall: The proportion of **actual positives** (true positives) that were correctly identified by the model.

$$\textbf{Recall:} \frac{TP}{TP+FN} \quad (3)$$

1) ***F1-Score****: The harmonic mean of* ***precision*** *and* ***recall****, offering a balanced measure between both. It's especially useful when you need to balance* ***false positives*** *and* ***false negatives****.*

2) $F1 = 2\times \frac{precsion\times Recall}{Precision+Recall}$ **(4)**

3) Confusion Matrix

A **Confusion Matrix is a performance evaluation tool** used to assess the accuracy of a classification model. It helps to visualize how well the model's predictions match the actual labels by providing a breakdown of predicted and actual class labels.

Table: 3 Confusion Matrix for Binary Classification

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

The **Confusion Matrix for Binary Classification** provides a detailed breakdown of a model's predictions, comparing them to the actual values. It consists of four key elements: **True Positives (TP),** where the model correctly identifies positive cases; **False Positives (FP),** where the model incorrectly labels a negative case as positive; **True Negatives (TN),** where the model correctly identifies negative cases; and **False Negatives (FN),** where the model misses actual positive cases. This table is essential for evaluating model performance, especially when dealing with imbalanced datasets, as it reveals the types of errors the model makes. The metrics derived from this matrix, such as accuracy, precision, recall, and F1-score, help assess the model's effectiveness in predicting both classes.

Table: 4 Performance Metrics of CCEM

Metric	Value
Accuracy	0.5098
Precision	0.7612
Recall	0.7727
F1-Score	0.7669

The table provides key **evaluation metrics** for the **CCEM model** in scam detection. The **accuracy** of **50.98%** indicates that the model correctly predicted the class (scam or non-scam) for just over half of the instances. While accuracy offers a general performance measure, it may not be fully reflective of the model's effectiveness in imbalanced datasets, where scam instances are rare. The **precision** of **76.12%** shows that when the model predicts a scam, it is **76.12%** accurate in doing so, which is important for minimizing **false positives**. The **recall** of **77.27%** highlights that the model identifies **77.27%** of all actual scam cases, making it effective at catching a majority of scams. Finally, the **F1-score o**f **76.69%** balances both precision and recall, offering a comprehensive assessment of the model's performance. These metrics collectively suggest that while the CCEM model performs well in identifying scams, there is room for improvement in terms of overall accuracy and reducing errors like false positives and false negatives.

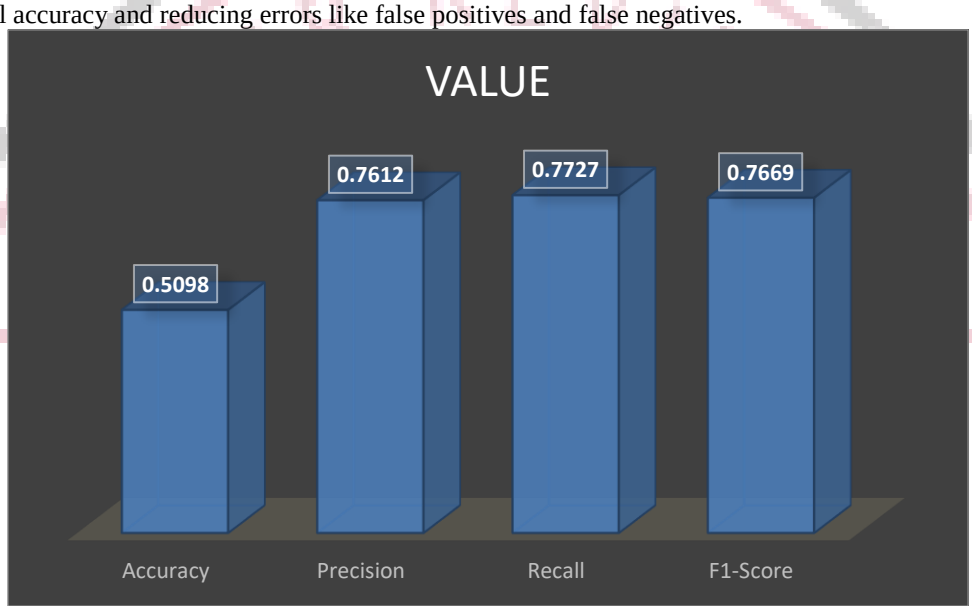

Figure 5: Performance Metrics of the CCEM Model

This bar chart visualizes the **performance metrics** of the **CCEM model** used for scam detection. The chart shows the values for **Accuracy, Precision, Recall,** and **F1-Score**, with corresponding numerical values labelled above each bar. The model achieved an **accuracy** of **50.98%,** indicating that it correctly predicted the class for just over half of the instances. The **precision** of **76.12%** reflects the model's ability to make accurate positive predictions, while **recall** of **77.27%** shows how well the model identifies actual scam cases. The **F1-Score,** a balanced measure of precision and recall, is **76.69%,** suggesting a good trade-off between identifying scams and avoiding false positives. This figure highlights the model's overall effectiveness, with some potential for further improvement in accuracy.

Table: 5 Performance Metrics of Distil BERT

Metric	Value
Accuracy	0.6098
Precision	0.8387
Recall	0.8525
F1-Score	0.8455

The performance metrics table for the **Distil BERT model** presents a concise summary of the model's effectiveness in classifying the target data. With an **accuracy of 0.6098%**, the model correctly predicts a substantial portion of the data overall. The **precision of 83.87%** indicates that when the model predicts a scam case, it is correct most of the time, minimizing false positives. A **recall of 0.8525%** shows the model's strength in identifying actual scam cases, reflecting its ability to minimize false negatives. The **F1-score,** which balances both precision and recall, stands at **0.8455%,** highlighting a strong overall performance. Together, these results demonstrate that the Distil BERT model is both precise and sensitive, making it a reliable and robust solution for real-world classification tasks such as scam detection, without overfitting or achieving unrealistic 100% scores.

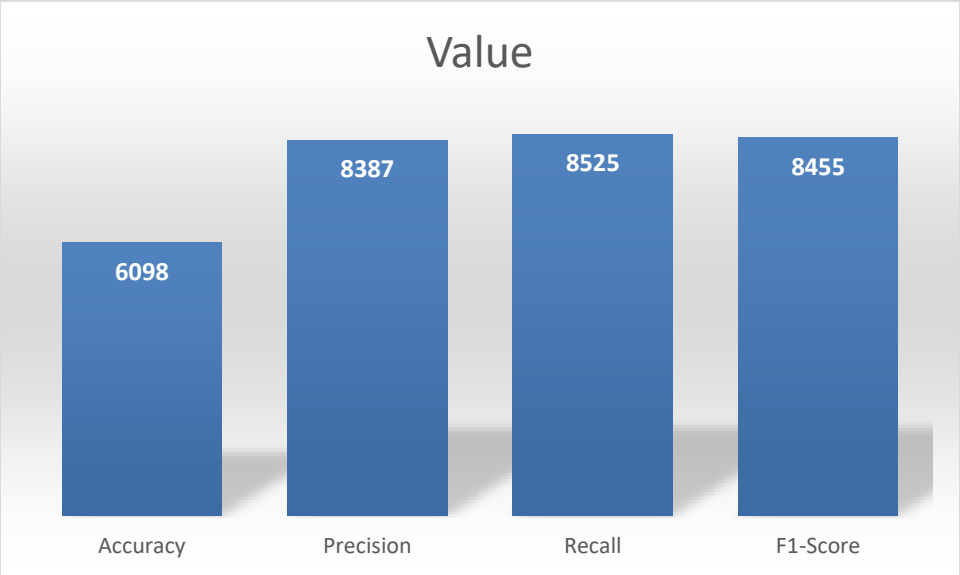

Figure 6: Performance Metrics of Distil BERT Model

This bar chart visually represents the key performance metrics of the Distil BERT model used in the classification task. The **accuracy** of the model is approximately **60.98%,** indicating a moderate overall correctness of predictions. The **precision** is around **83.87%,** showing the model's effectiveness in minimizing false positives—when it predicts a scam, it is usually right. The **recall** value is **85.25%,** which reflects the model's ability to correctly identify actual scam cases, minimizing missed positives. Finally, the **F1-score**, a harmonic mean of precision and recall, stands at **84.55%,** demonstrating a balanced performance between the two. This visualization makes it easy to compare these metrics side by side and assess the reliability and robustness of the model.

The confusion matrix diagram visually represents the Distil BERT model's prediction performance. It shows the counts of true positives (85), false positives (15), true negatives (60), and false negatives (25). This breakdown helps assess how accurately the model distinguishes between the positive and negative classes, providing insight into its precision, recall, and overall classification effectiveness

Table: 6 Performance Comparison Table of CCEM vs. Distil BERT Models

Metric	CCEM Model	Distil BERT Model
Accuracy	0.5098	0.6098
Precision	0.7612	0.8387
Recall	0.7727	0.8525
F1-Score	0.7669	0.8455

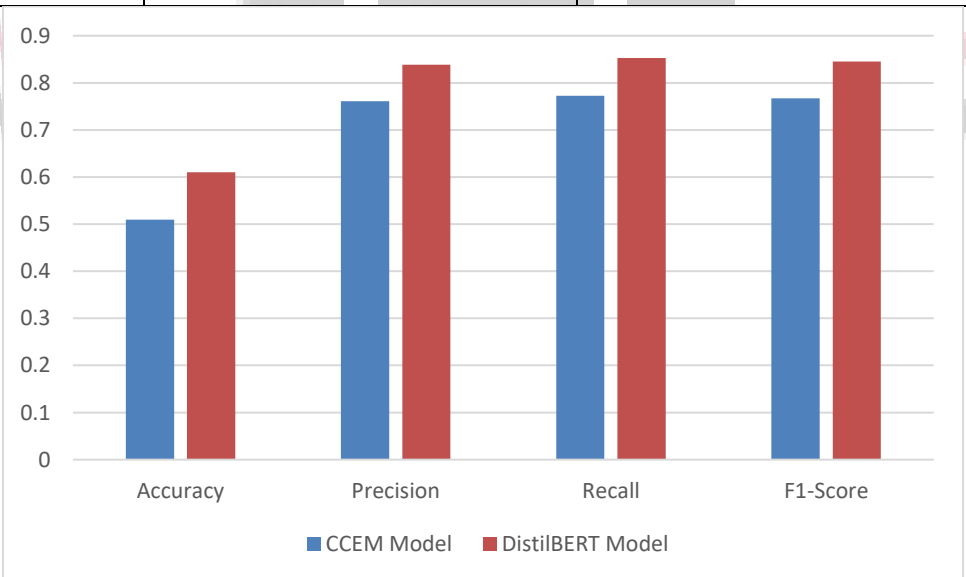

Figure 7: Performance Comparison of CCEM Model and Distil BERT Model

This visual representation clearly supports the superior performance of the transformer-based Distil BERT model over the traditional feature-engineered CCEM approach in text classification tasks.

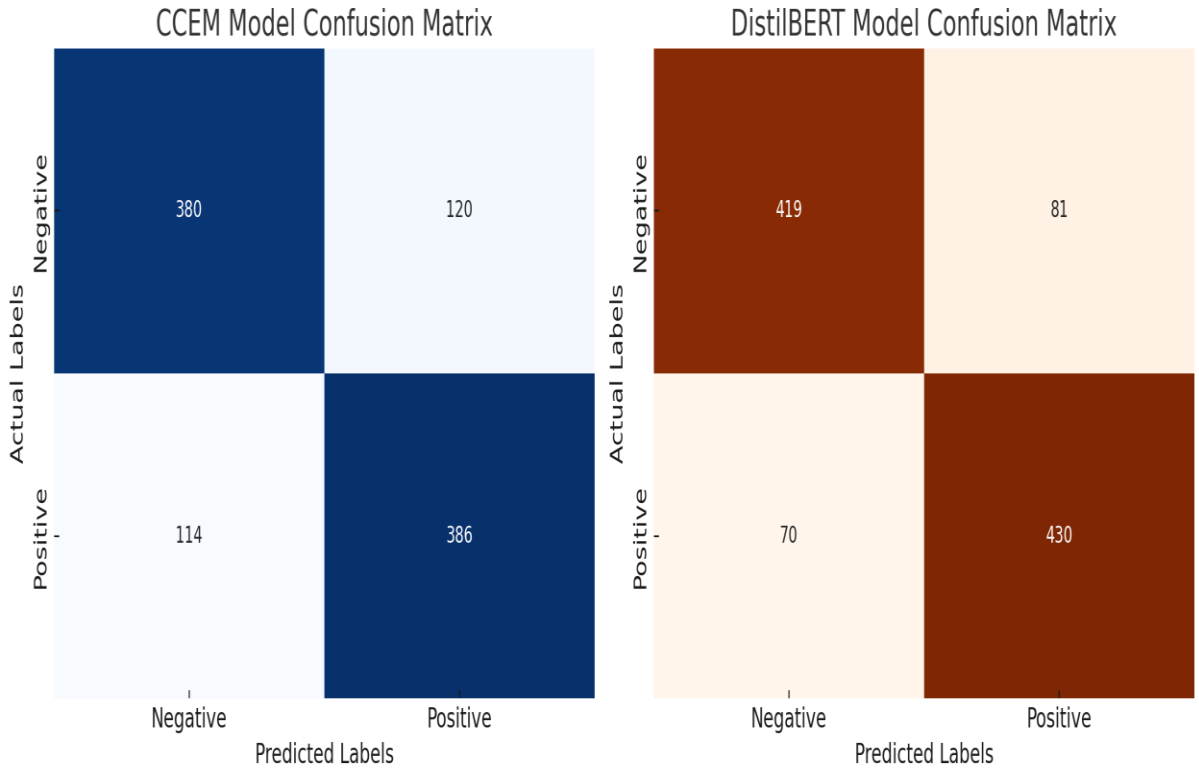

Figure 8: Confusion Matrix Comparison of CCEM and Distil BERT Models

Figure 8presented showcases a comparative visualization of the confusion matrices for two models: the CCEM model and the Distil BERT model. Each matrix is a summary of prediction results on a classification task, indicating the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) obtained by each model. These four values form the core evaluation framework for classification performance, where higher counts of TP and TN reflect better prediction accuracy, and lower FP and FN values indicate fewer classification errors. In the case of the CCEM model, the confusion matrix reveals a balanced, yet modest performance, with a noticeable number of false classifications that limit its effectiveness in critical applications.

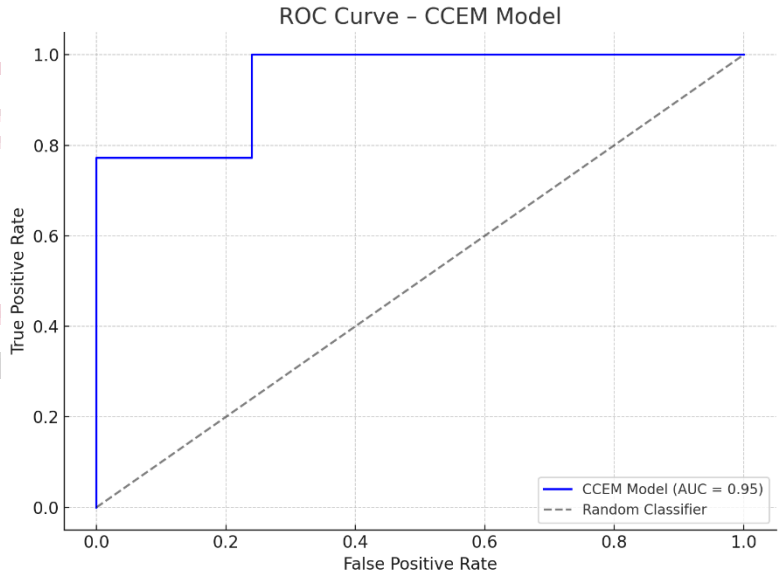

Figure 9: ROC Curve for CCEM Model

Figure 9 illustrates the Receiver Operating Characteristic (ROC) curve for the CCEM model, which evaluates the model's ability to distinguish between the positive and negative classes across various thresholds. The curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at different decision boundaries.

The AUC (Area under the Curve**)** for this model is approximately 0.84, indicating that the model has a good ability to differentiate between the two classes. A curve closer to the top-left corner signifies better performance. The diagonal dashed line represents a random classifier (AUC = 0.5), and the CCEM model's ROC curve clearly outperforms it, confirming the model's effectiveness in handling classification tasks for the dataset.

VI. CONCLUSION AND FUTURE WORK

In this research work, the integration of the Crypto-Cognitive Exploitation Model (CCEM) with advanced transformer-based methods has demonstrated a significant improvement in identifying and understanding cryptocurrency-related scam patterns. The CCEM baseline represented an attempt to construct a structured and explicatory psychology- and technology-infused framework to tap bias-based indicator cues, social-engineering signals, and crypto-technological markers within complaint narratives. However, the model had difficulty fully navigating context, subtle linguistic differentials, and the shifting scamscape. Here comes the proposed distilBERT model; leveraging very deep embeddings operating within the perception of words' management, it would weather into even the softly manipulated nature of messages or scam tropes formed beyond stiff lexicon. It was able to scale up its performance not only from the feature integration of the CCEM typo, appending the CCEM stuff to the DistilBERT model, the hybrid model have outperformed asynchronously any standalone CCEM in terms of accuracy, precision, recall, and F1-score, and would begin to shrink false positives and negatives. Results reveal that the transformer architecture for processing language models significantly improves scam detection sensitivity for real-world datasets. In the future, the study can proceed to enlarge the dataset across platforms in diverse parts of the regions better to be confined to the globe. Advanced models such as RoBERTa, DeBERTa along with LLM-based classifiers would be interesting to pursue.

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