International Journal of Advanced Trends in Engineering and Management
(ISSN 2583-7052)

Vol. II, No. 07, pp. 28-36, July

A Coati optimization Algorithm Enhanced Vision Mamba Framework for Social Media App Usage Classification

Subbulakshmi M K[1], Deepthi S S[4]

[1]Assistant professor, Department of Master of Computer Applications, Francis Xavier Engineering College, Vannarapettai, Tirunelveli, Tamil Nadu, India - 627003.

[4]Assistant professor, Department of Information Technology, Francis Xavier Engineering College, Vannarapettai, Tirunelveli, Tamil Nadu, India - 627003. deepthi@francisxavier.ac.in

Corresponding Author E-mail: subbulakshmimk@francisxavier.ac.in

ABSTRACT: Social Media (SM) applications have increased the importance of analysing and classifying user's SM usage patterns. However, variations in user behaviour, missing data, outliers, and complex relationships among usage-related features affect classification performance. To overcome these challenges, this paper proposes a Coati Optimization Algorithm-Enhanced Vision Mamba (COA-VM) Framework for SM app usage classification. Gen-Z social media usage dataset undergoes pre-processing, containing missing-value handling and outlier detection, to improve data quality. Feature standardization is then executed to bring the input variables to a consistent scale. Exploratory Data Analysis (EDA) and feature correlation analysis are subsequently conducted to examine data distributions and detect relationships among the relevant features. The proposed VM-based classification framework to learn complex patterns associated with SM application usage and predicts the corresponding usage categories. The COA optimizes VM parameters and improves its predictive performance. Experimental outcomes is implemented in Python software using Gen-Z social media usage dataset, contains 95.57% of accuracy, 96.15% of recall, 95.85% of F1-score and precision, then 98% of AUC-ROC. The proposed COA-VM method provides an effective and reliable classification mechanism for analysing SM app usage patterns.

Keywords: Social Media, Coati Optimization Algorithm, Vision Mamba, Exploratory Data Analysis

1. Introduction

The rapid growth of SM during the past two years have significantly changed the way people communicate, exchange information, and discuss personal and global issues [1]. Consequently, platforms [2] like Facebook, X (formerly Twitter), Instagram, and YouTube attract billions of users and generate enormous amounts of user-created content that spread rapidly worldwide [3]. Whereas these platforms encourage communication, information sharing, and community participation, they have also contributed to the spread of harmful and abusive content [4-5]. For this several techniques are utilized for SM app usage classification. In [6] a Capsule Network (CapsNet) and Long Short-Term Memory (LSTM) model is used to classify SM application usage patterns. It identifies different SM usage patterns from user activity data. However, CapsNet and LSTM increase training, low performance. Furthermore, in [7] Bidirectional Encoder Representations from Transformers (BERT) and a Feedforward Neural Network (FNN) is used for social bot detection. BERT captures the contextual meaning of words in SM posts. Nevertheless, text-based analysis did not capture account activity, posting frequency, interaction patterns.

2. Related Works

For SM app usage classification various techniques are used for detection. In [8] Ahmed et al (2026) have proposed LSTM and Bidirectional LSTM (Bi-LSTM) with Word2Vec to learn sequential and contextual patterns in textual data, fine-tuned DistilBERT to capture deeper contextual relationships and improve text representation. Nonetheless, multiple models require real-time deployment more difficult. Consequently, in [9] Riaz et al (2024) have presented LSTM and Transformer (TransLSTM) for suggestion mining. It identifies implicit and explicit suggestions in user-generated content. However, Performance depends on the quality and diversity of labelled suggestion-mining datasets. Additionally, in [10] Fethi et al (2025) have developed fine-tuned XLM-RoBERTa transformer to detect and classify hate speech in SM text. It supports hate speech detection across multiple languages. However, detection performance is lower for languages with limited training data. Furthermore, in [11] Qasim et al (2025) have proposed RoBERTa- base to detect and classify SM content. It distinguishes among predefined types, like hateful and non-hateful content. Nevertheless, it suffers with sarcasm, slang, coded expressions, and implicit harmful language. Moreover, in [12] Arshad et al (2026) have invented Gated Recurrent Units (GRU) with an attention mechanism to evaluate and classify SM content. GRU-Attention model adapted to detect hate speech, offensive language, and other harmful content. Nonetheless, GRU have difficulty retaining information across very long text sequences.

2.1 Problem Statement

The growing uses of SM applications have created a need for exact classification of user application usage patterns. Existing classification methods suffer to capture these complex patterns, potentially reducing predictive accuracy and generalization. Furthermore, the performance of DL models is affected by inappropriate parameter selection. Consequently, an intelligent classification structure is essential to improve data quality, learn complex usage patterns, and optimize model parameters. To overcome these limitations, this paper proposes a COA-VM structure for classifying Gen-Z social media application usage patterns.

2.2 Contribution of the Work

Data pre-processing used to handle missing values and detect outliers in the Gen-Z social media usage dataset, improving data quality and consistency. A proposed VM is developed to learn complex patterns and dependencies in SM usage features and classify users into the corresponding application usage categories. COA optimizes the selected VM parameters, to improve classification performance for SM app usage.

3. Proposed Methodology

To classify Gen-Z SM application usage patterns through an optimized DL method this paper proposed COA-VM framework. At first, the Gen-Z social media usage dataset is pre-processed by handling missing values and identifying outliers to improve data quality and consistency. Consequently, EDA based on feature correlation analysis are implemented to examine data distributions, identify usage trends, and understand relationships among the input features. Feature standardization is then applied to bring the input variables to a common scale. The pre-processed features are then delivered to the VM model, which learns complex patterns and dependencies associated with SM application usage and predicts the corresponding usage classifications. To improve classification performance, the COA optimizes the selected VM parameters by exploring suitable parameter configurations and identifying an effective solution based on the classification for SM app usage. Figure 1 displays the proposed block diagram for SM app usage classification.

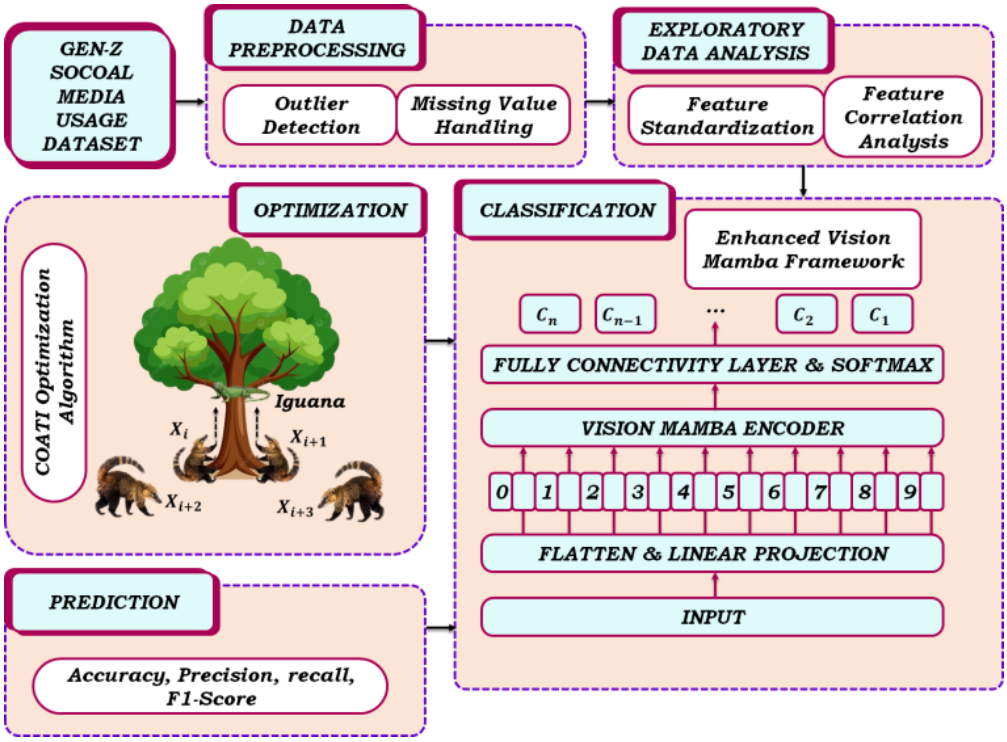


Figure 1: *Proposed block diagram for SM app usage*

3.1 Data Pre-processing

For SM app usage missing-value handling is implemented by detecting incomplete entries and replacing missing numerical values using suitable statistical measures. For unconditional variables, missing entries is replaced with the mode it helps to preserve useful records whereas improving dataset completeness. Outlier detection is then conducted to identify unusually high or low values in usage-related features, like application usage frequency, session duration, and interaction counts. Identified outliers are examined and where appropriate, treated through removal or capping to reduce their influence on the classification process.

3.2 Exploratory Data Analysis

For SM app usage EDA is performed to understand the characteristics and patterns within the Gen-Z social media app usage dataset before model training. It involves examining feature distributions, identifying usage trends, and detecting unusual patterns. Feature correlation analysis is conducted to understand the relationships among numerical input variables. A correlation heatmap show whether two features have a positive, negative, or weak relationship. This analysis identifies related features, potential redundancy, and important relationships within the dataset.

Feature standardization is applied to transform numerical input variables to a common scale. SM usage features have different ranges and units like screen time is measured in hours, application frequency in counts, and session duration in minutes. Features with larger numerical values have an excessive influence during model training. Standardization normally uses the subsequent calculation

$$X_{standardized} = \frac{X-\mu}{\sigma} \quad (1)$$

Where, X signifies the original feature value, μ denotes the mean of the feature, σ indicates its standard deviation. After standardization, each numerical feature nearly zero mean and unit variance. This provides consistently scaled inputs to the VM model and supports stable model training.

3.3 Enhanced Vision Mamba Framework

For SM app usage classification VM framework uses its selective state-space mechanism to capture dependencies among the input features. It selectively processes relevant information whereas maintaining computational efficiency, allowing the model to learn patterns associated with SM usage behavior. Figure 2 shows the structure of VM model.

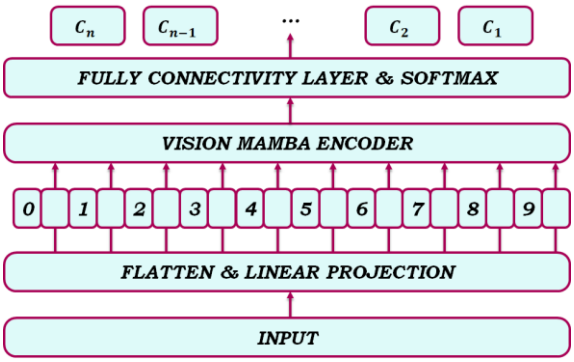


Figure 2: *Structure of VM model*

The learned feature representations are then passed to a classification layer, which predicts the corresponding SM application usage categories. The learned feature representations are subsequently passed through fully connected layers to diagnosis the engine fault. The hidden state is efficient by the equation

$$h_t = Ah_{t-1} + Bx_t \tag{2}$$

Where, h_t specifies hidden state at time t, A identifies state transition matrix, B indicates input projection matrix, x_t denote input vector. The VM network selectively updates its internal state by

$$h_t = f(h_{t-1}, x_t, \theta) \tag{3}$$

Where, $f(\cdot)$ indicates the selective state-space function, θ represents the learnable network parameters. The classified VM is said as

$$\hat{y} = Wh_t + b \tag{4}$$

Where $\hat{y}$ identifies classified SM, W indicates output weight matrix, b denote bias vector. The VM reduces complexity whereas efficiently learning complex patterns and dependencies among SM app usage features. To fine-tune the VM parameters COA is utilized.

Coati Optimization Algorithm

COA optimizes the VM parameter for SM app usage classification. The COA generates a population of candidate solutions, where each candidate represents a possible configuration of the selected VM parameters. Figure 3 displays the flowchart for COA.

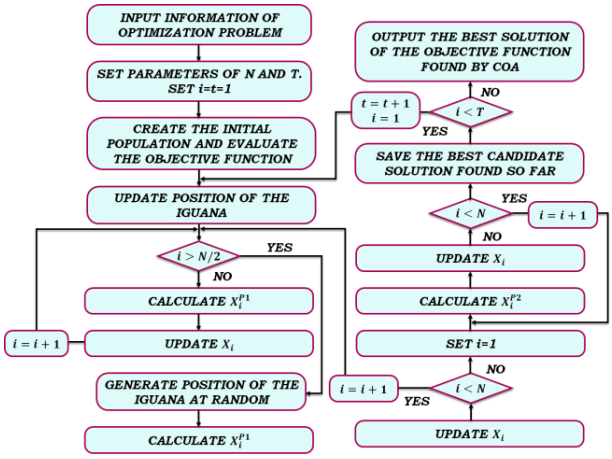


Figure 3: *Flowchart for COA*

Stage 1 Population Initialization

The COA begins by generating N candidate solutions within a D dimensional search space, whereas ensuring that each solution satisfies the predefined $[lb, ub]$.

$$X_{i,j} = lb_j + r.(ub_j - lb_j) \tag{5}$$

Where, $r \sim U(0,1)$ represent a uniformly distributed random number.

Stage 2 Hunting and attacking approach (Exploration)

First Half: The first half of the populace updates its locations by moving towards the current global best solutionX_{best}, which is represented by the iguana positioned on a tree.

$$i = 1, \ldots . \frac{N}{2} \tag{6}$$

$$X_i^{new} = X_i + r.(X_{best} - I.X_i) \tag{7}$$

Where, $r \sim U(0,1)$ and $I = round\ (1 + r')$ with $r' \sim U(0,1)$

Second Half($i = \frac{N}{2} + 1, \ldots, N$): For the second half of the populace, COA randomly generates an iguana position X_{iguana} within the predefined search boundaries and evaluates its fitness F_{HL}. The position-update strategy is then selected based on the fitness evaluation among the random iguana and the current search agent for SM app usage.

$$X_i^{new} = \begin{cases} X_i + r.(X_{iguana} - I.X_i) & if\ f(X_i) > F_{HL} \\ X_i + r.(X_i - X_{iguana}) & if\ f(X_i) \leq F_{HL} \end{cases} \quad (8)$$

Stage 3 Escaping from Predators (Exploitation)

During the exploitation stage, COA simulates the coatis escape from killers by refining candidate solutions through local searches within progressively narrowing search boundaries.

$$LO_t = \frac{lb}{t}, HI_t = \frac{ub}{t} \quad (9)$$

$$X_i^{new} = X_i + (1 - 2r).(LO_t + r'.(HI_t - LO_t) \quad (10)$$

Where, t indicates the present iteration number

Stage 4 Greedy Selection

After every stage, a greedy selection strategy compares the updated solution with the existing one and retains the candidate with better fitness.

$$X_i = \begin{cases} X_i^{new} & if\ f(X_i^{new} < f(X_i) \\ X_i & otherwise \end{cases} \quad (11)$$

Through its exploration and exploitation search mechanisms, COA updates the candidate solutions to identify parameter configurations that improve classification performance. The best-performing configuration is then used to train the optimized VM model, which predicts the consistent Gen-Z SM application usage classifications.

4. Result and its discussion

For SM app usage classification the proposed COA-VM model is implemented in Python software using Gen-Z Social Media Usage Dataset. The dataset contains 1,000,000 samples and 12 features, providing a substantial set of usage-related information for model development and evaluation. The dataset is divided into training and testing subsets using an 80:20 ratio.

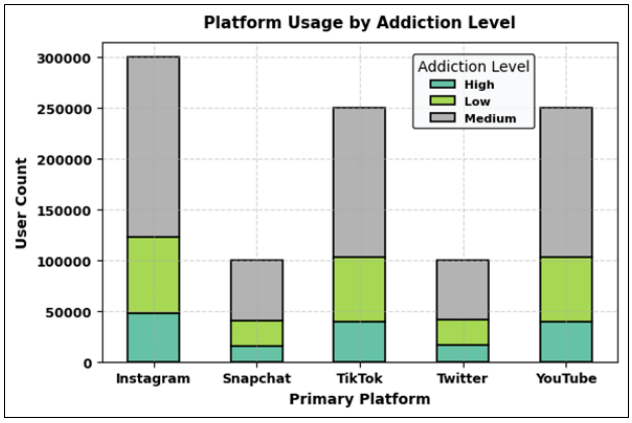


Figure 4: *Platform usage by addiction level*

Figure 4 displays the platform usage by addiction level, Instagram have the highest overall user count (nearly 300,000), whereas Snapchat and Twitter have the lowest (nearby 100,000 each). Across all five platforms, Medium addiction represents the largest user group, followed by Low and High addiction levels. TikTok and YouTube show nearly identical distributions, with around 250,000 users each.

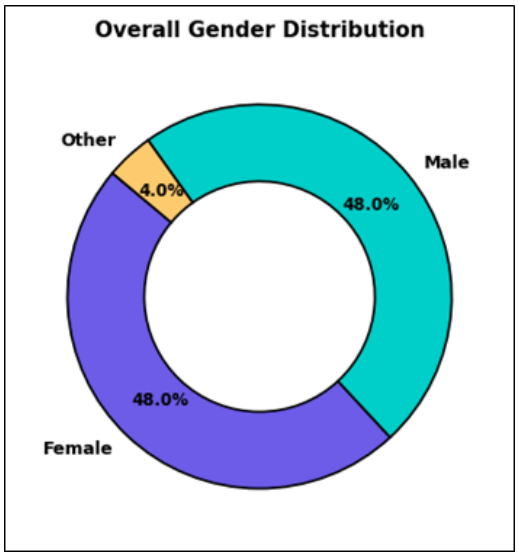


Figure 5: *Overall gender distribution*

Figure 5 shows the overall gender distribution. The male and female each have the count of 48% and other have the count of 4% for classifying SM app usage.

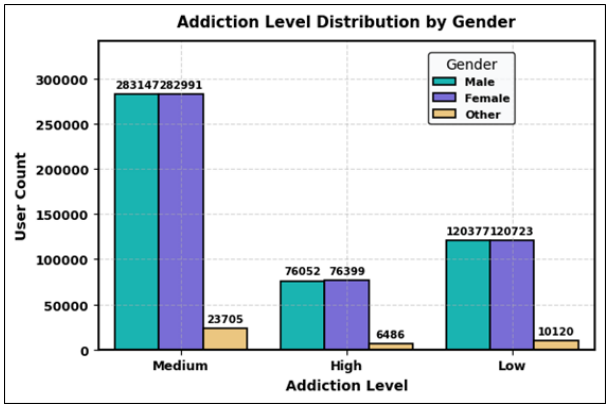


Figure 6: *Addition level distribution by gender*

Figure 6 displays the addition level distribution by gender. Medium addictions have the highest user count, with 283,147 males, 282,991 females, and 23,705 users in the other category. Low addiction follows with 120,377 males, 120,723 females, and 10,120 other users. High addiction has the lowest count, comprising 76,052 males, 76,399 females, and 6,486 other users. Male and female distributions are nearly equal across all three levels for SM app usage classification.

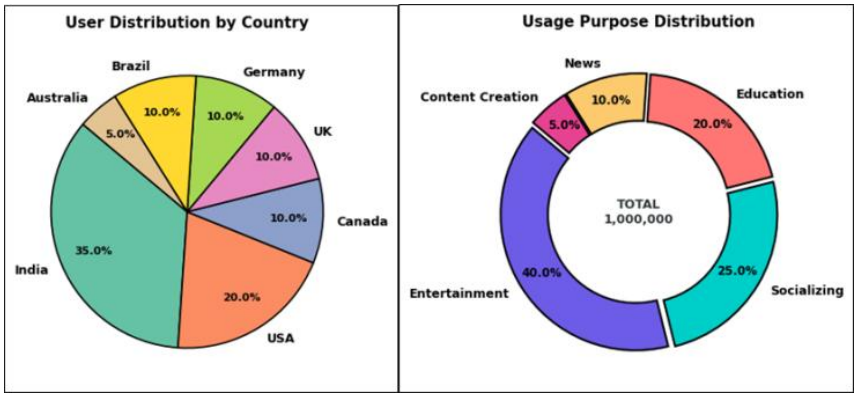


Figure 7: *User distribution by country & usage purpose distribution*

Figure 7 displays user distribution by country, showing that India denotes the largest market share at 35.0%, followed by the USA at 20.0%. Germany, the UK, Canada, and Brazil each hold an equal share of 10.0%, whereas Australia accounts for the smallest slice at 5.0%. Usage purpose distribution, illuminating that entertainment is the primary driver for users at 40.0%. Socializing creates up a quarter of the activity at 25.0%, followed closely by education at 20.0%, news at 10.0%, and content creation accounting for the smallest portion at 5.0%.

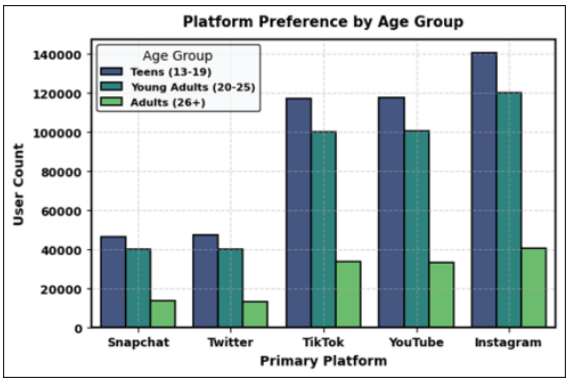


Figure 8: *Platform preference by age group*

Figure 8 shows the platform preference by age group. The teens (13–19) have the highest social media usage, followed by young adults (20–25) and adults (26+). Instagram is the most popular platform, with over 140,000 teen users and nearly 120,000 young adult users. TikTok and YouTube each have around 118,000 teen users and 100,000 young adult users. Snapchat and Twitter are less preferred, with fewer than 50,000 users in their highest age group for SM app usage classification.

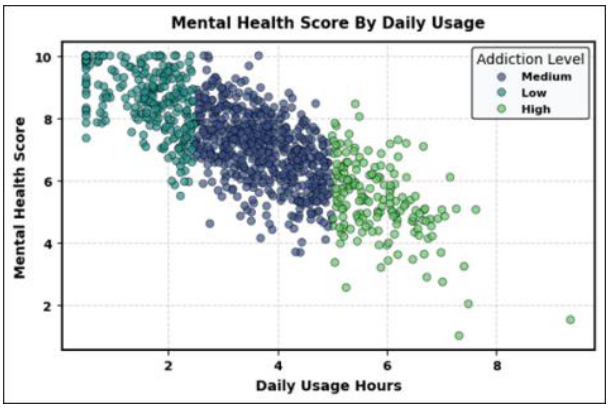


Figure 9: *Mental health score by daily usage*

Figure 9 displays mental health score by daily usage, it shows a negative relationship between SM usage and mental health scores. Low-addiction users spend 0.5–2.5 hours with scores of 7–10, medium-addiction users spend 2.5–5 hours with scores of 5–9, and high-addiction users spend 5–7.5 hours with scores of 1–7. Whereas increased SM usage is related with lower mental health scores.

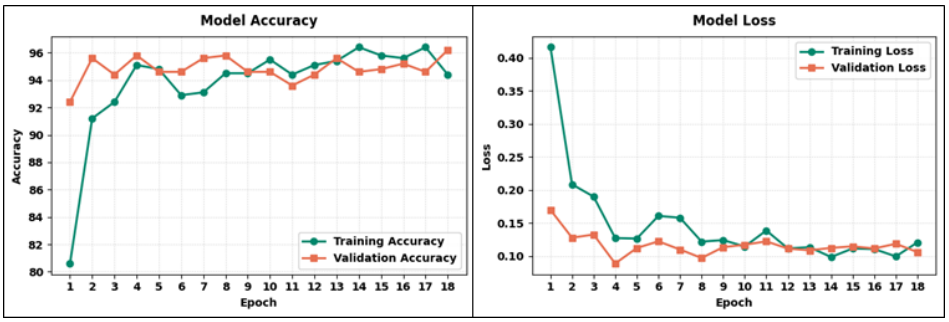


Figure 10: *Model accuracy & loss*

Figure 10 shows the model accuracy and loss with good convergence over 18 epochs. Training accuracy increases from 80.5% to 93–96.5%, closely matching validation accuracy. Training loss decreases from 0.42 to below 0.15 within the first four epochs. The close alignment of training and validation curves specifies good generalization with no significant overfitting.

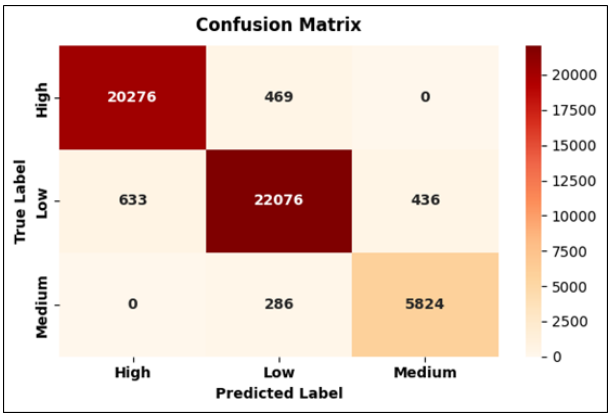


Figure 11: *Confusion matrix using COA-VM model*

Figure 11 displays confusion matrix using COA-VM for SM app usage classification. The strong classification performance across three classes high with 20,276, low with 22,076, and medium with 5,824 correctly predicted occurrences. Minor misclassifications include 633 low cases predicted as high and 436 low cases predicted as medium. The strong diagonal values specify that the model accurately distinguishes the three classes for SM app usage classification.

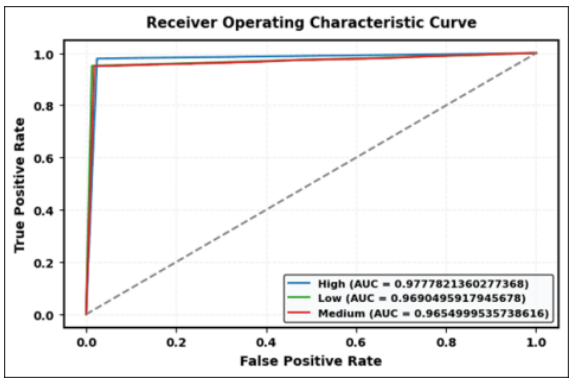


Figure 12: *ROC curve using COA-VM*

Figure 12 shows the ROC curve matrix using COA-VM for SM app usage classification. It demonstrates excellent classification performance, with AUC values of 0.978 for high, 0.969 for low, and 0.965 for medium. All three curves approach a true positive rate of 1.0 with a very low false positive rate, indicating that the model effectively distinguishes all three classes with high predictive accuracy.

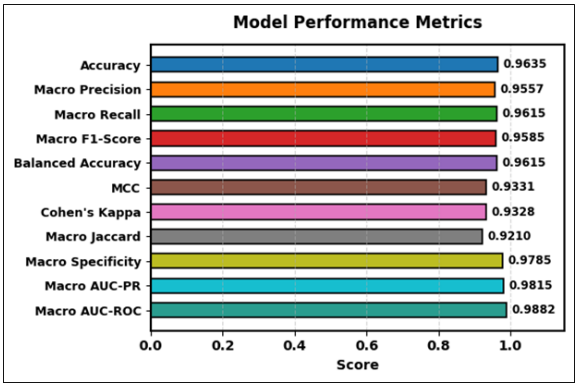


Figure 13: *Model performance metrics*

Figure 13 shows model performance metrics using COA-VM for SM app usage classification. The model demonstrates excellent classification performance, attaining 96.35% accuracy, 95.57% precision, 96.15% recall, and 95.85% F1-score. It also achieves high AUC-ROC of 0.9882, AUC-PR of 0.9815, and specificity of 0.9785. The MCC of 0.9331, Cohen's Kappa of 0.9328, and Jaccard score of 0.9210 the model have strong reliability and classification consistency.

Comparison with the proposed technique

In the evaluation with proposed technique the proposed COA-VM method is related with the existing techniques as presented in table 1.

Table 1: *Comparison with the proposed technique*

Study	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Fetahil et al [10]	85.4	85.4	85.4	85.4
Awan et al [6]	86	83.3	80	81.6
Qasim et al [11]	91	90	90	90
Suksam et al [1]	93.9	94	93.9	93.9
Sallah et al [7]	94	92	92	90
Proposed Work	95.57	96.15	95.85	95.85

Fetahil et al [10] have the accuracy of 85.4%, 85.4% of precision, recall and F1-score, Awan et al [6] have the 86% of accuracy, 83.3% of precision, 80% of recall, 81.4 % of F1-score, Qasim et al [11] have the 91% of accuracy, 90% of precision, recall, F1-score, Suksam et al [1] have the 93.9% of accuracy, 94% of precision, 93.9% of recall, F1-score , Sallah et al [7] have the 94% of accuracy, 92% of precision and recall, 90% of F1-score , then the higher value with 95.57% of accuracy, 96.15% of recall, 95.85% of F1-score and precision using proposed COA-VM model for SM app usage classification.

5. Conclusion

For accurate and reliable SM application usage classification COA-VM structure is proposed and implemented using the Gen-Z social media usage dataset. The data pre-processing stage improve the data quality, feature standardization, exploratory data analysis, and correlation analysis with VM for effective feature learning and classification. The COA optimizes the VM model parameters to improve classification performance. Experimental results validate 95.57% accuracy, 96.15% recall, 95.85% F1-score, 95.57% precision, and 98% AUC-ROC. These results highlight the effectiveness of the proposed COA-VM framework in identifying complex SM usage patterns and providing reliable classification performance.

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