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An Adaptive Conv-Transformer Network with Whale Optimization for Social Media Engagement Classification

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ABSTRACT: Social media engagement classification uses data tools to sort user actions like likes, shares, and comments. This process helps brands understand customer behaviour, deliver personal content, and build stronger connections. In this paper, an Adaptive Conv-Transformer Network (ACTN) with Whale Optimization Algorithm (WOA) is proposed for social media engagement classification. Feature transformation is a data preprocessing step that applies mathematical functions to change raw data values into a new format. Data visualization turns complex social media metrics into clear graphics. It helps sort user interactions like likes, shares, and comments into distinct engagement classes. An ACTN extracts local spatial patterns and global contextual dependencies from text, images, or user interaction sequences, classifying social media engagement levels (such as high, medium, or low interaction) with high accuracy. The WOA improves social media engagement classification by acting as a smart feature selector and hyperparameter tuner. The performance analysis is carried out using python software and assesses the model's performance using key metrics such as precision, recall, F1-score, confusion matrix, and ROC-AUC. The proposed ACTN-WOA uses four classes, they are high, low, medium and viral. The proposed ACTN-WOA achieves high accuracy of 96% and better convergence speed. The proposed method outperforms conventional techniques, contributing a robust and reliable tool for social media engagement classification.

Keywords: Adaptive Conv-Transformer Network (ACTN), Whale Optimization Algorithm (WOA), Social media engagement classification.

1. Introduction

Social media data engagement is the collection, measurement, and analysis of user interactions such as likes, comments, shares, and clicks on digital platforms [1]. It helps groups track public interest, judge content performance, and understand how audiences connect with a brand [2,3]. Technology developments like social media and the internet, as well as generational shifts like the shift from Generation X to Generation Y, are examples of how this process is continuously evolving [4]. Research changes must take into consideration how these advancements affect customer decisions.

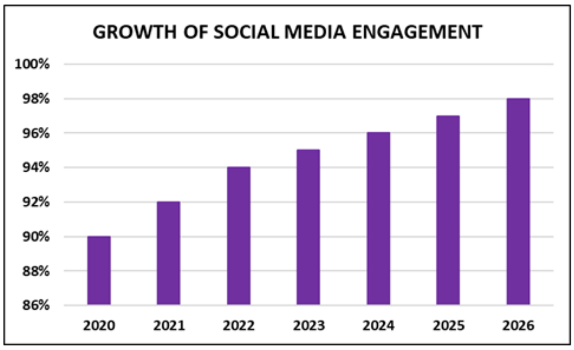

Figure 1: *Growth of Social Media Engagement*

The rise in social media usage is depicted in Figure 1. With the idea of engagement enabling users to become increasingly involved in producing the content that influences one another's decisions, social media has transformed the consumption process into a participatory phenomenon [5]. Nonetheless, a large portion of this crucial field's research focuses on Western countries' Generation Y population, who is thought to be spearheading the digital revolution in purchasing habits. For marketers who build tactics for developing nations based on study findings from the rich world, this presents an intriguing conundrum [6]. The cultural, political, and economic disparities found in these developing markets are not sufficiently taken into consideration by these techniques. In order to address the dearth of literature on the developing world, this chapter offers a critical review of the literature and makes recommendations for future directions for structural research on the topic within the Generation Y cohort of developing countries in Latin America and the Caribbean, a region that is heavily targeted by multinational corporations and whose citizens are becoming more and more consumerist [7]. The conventional techniques such as Adaptive Graph Convolutional Recurrent Network with Transformer and Whale Optimization Algorithm (AGCRN-T-WOA) [8], Deep Neural Network with Feedback Mechanism (DNN-FM) [9] and Generative Adversarial Network with Graph Neural Network (GAN-GNN) [10] have been used for social media engagement classification. These techniques have some disadvantages like low convergence speed, less reliability and High response time. To avoid these issues, an ACTN-WOA is proposed for social media engagement classification. The contribution of the paper is as follows,

- Data visualization is used to transform complex numerical metrics and categorical model predictions (such as likes, shares, sentiments, and high or low engagement groups) into intuitive visual formats.
- ACTN-WOA is proposed for social media engagement classification to accurately predict and categorize user interactions by automatically extracting complex data patterns and fine-tuning model settings.

2. Recent Works

Social media engagement classification using AGCRN-T-WOA networks have been presented in [8] to analyse social media engagement classification. It combines graph learning, sequence modeling, and smart tuning to capture complex user interaction patterns. captures complex user interactions over time while automatically finding the best model settings to boost prediction accuracy and speed. However, this mix brings high computing costs, slow training times, and a high risk of overfitting on noisy data. The hybrid DNN-FM have been proposed in [9] for social media classification. DNN-FM struggle with social media engagement due to high computational costs, slow training times from sequential processing, difficulty handling sudden slang shifts, and vanishing gradients that lose long-term context in fast-moving text threads. [10] presented the GAN-GNN for social media analysis, which improves social media engagement classification by generating realistic synthetic data to fix class imbalances, modeling complex user-connection structures, and enhancing resistance against adversarial attacks and fake account manipulation. However, it produces high computational costs, severe training instability, data sparsity issues, and vulnerability to adversarial attacks, making real-time deployment difficult and model optimization complex. To overcome these drawbacks, an ACTN-WOA is proposed in this paper for social media engagement classification.

3. Proposed Work Explanation

The proposed block diagram of ACTN-WOA for social media engagement classification is represented in figure 2. The process begins with the social media engagement dataset, which immediately undergoes a data quality assessment to evaluate the baseline integrity of the raw input. Following this initial assessment, the data is split into two parallel processing tracks, they are missing value analysis to handle incomplete records, and a data consistency check to ensure formatting and logical uniformity. Once these tracks converge, the unified data moves into a noise reduction stage to filter out random variances and irrelevant background information. The process then branches again into two concurrent refinement steps, such as outlier handling to manage extreme values, and robust scaling to normalize data features while minimizing the influence of those outliers.

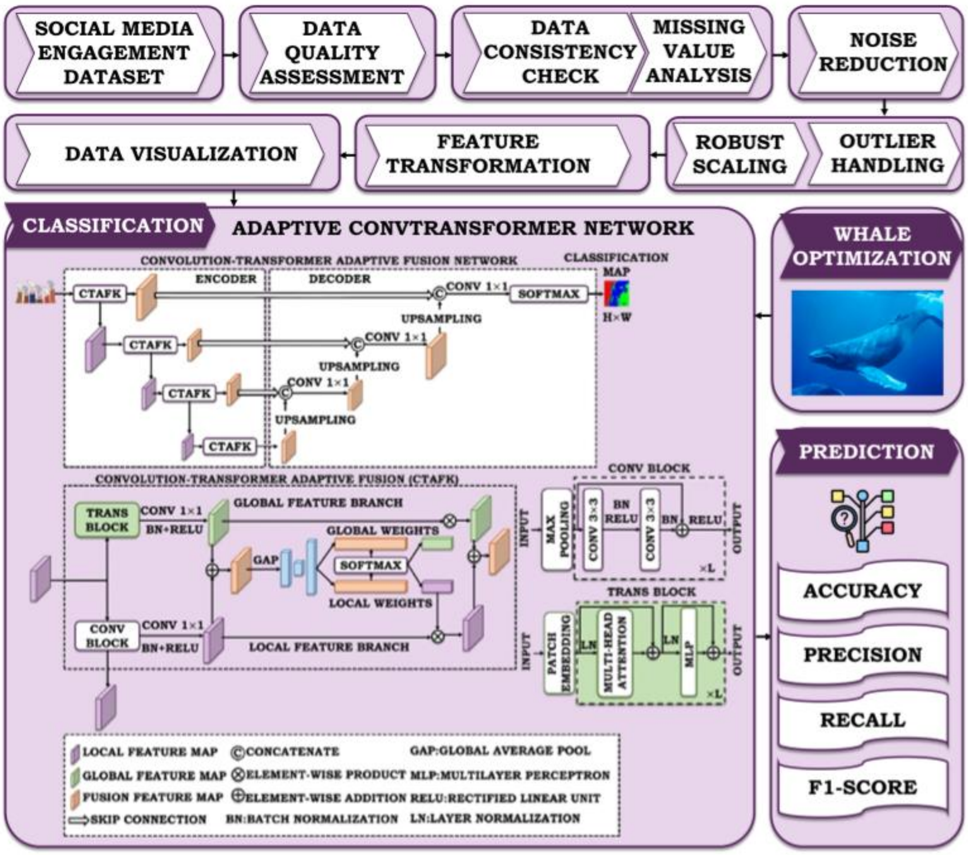

Figure 2: *Proposed block diagram of ACTN-WOA for social media engagement classification*

After these scaling and cleaning steps converge, the data enters the feature engineering and modelling phases. It progresses sequentially through feature transformation to prepare variables for mathematical optimization, data visualization to inspect distributions or patterns visually, and classification to categorize the underlying data structures. This structured information is then fed into an advanced neural architecture called the ACTN. This network's performance and parameter weights are simultaneously enhanced by a WOA block. Finally, the optimized system outputs a definitive prediction, completing the end-to-end data processing and inference workflow.

3.1. Modelling of Data Visualization

The process of turning raw numbers into clear pictures like charts and graphs is named as data visualization. To calculate key values, map coordinates, and show trends so people can understand information quickly, data visualization uses math formulas.

Mathematical expression for mean (average) to check data center:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (1)$$

Mathematical expression for min-max feature scaling:

$$x_{normalized} = \frac{x_i - \min(X_{train})}{\max(X_{train}) - \min(X_{train})} \quad (2)$$

Crucially, the min and max values are calculated only from the training data (X_{train}). The same parameters are then used to transform the test data.

Choose variables for the X and Y axes and convert data points to pixel coordinates on a screen. Linear scaling equation for pixel position is derived as:

$$P = \frac{x - x_{Min}}{x_{Max} - x_{Min}} \times pixelwidth \quad (3)$$

Instead of scanning through thousands of rows in a spreadsheet, visualization tools convert data into intuitive shapes and colors, making systemic flaws immediately apparent. An ACTN is used after initial visualization or feature extraction to dynamically capture global context and complex long-range dependencies that standard convolutional filters miss. It refines visual or spatial data by adjusting to varying shapes, noise, or multi-scale structures.

3.2. Mathematical modelling of ACTN

The Adaptive ConvTransformer network merges Convolutional Neural Networks (CNNs) and Transformers. It uses convolutional layers to capture local spatial features and self-attention mechanisms to learn global context. An adaptive gate dynamically balances both representations based on input content. Architecture of ACTN is represented in figure 3.

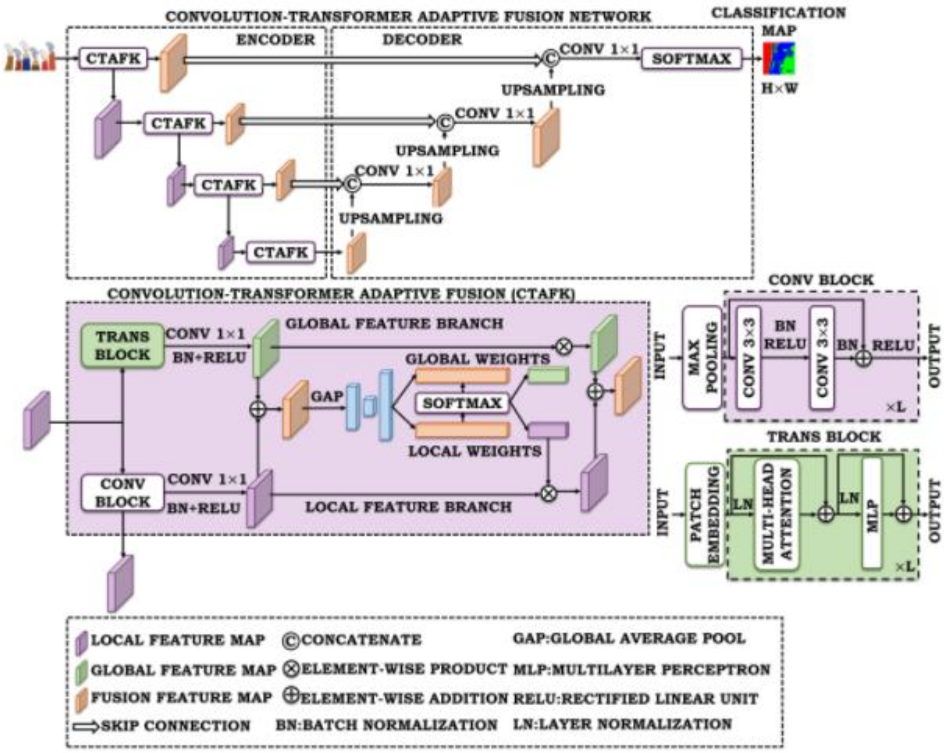

Figure 3: *Architecture of ACTN*

3.2.1 Input Representation and Local Feature Extraction:

The network receives an input tensor X in $X \in R^{B \times C \times H \times W}$. Local features are extracted using standard spatial convolutions. Input tensor X passes through a convolutional layer. Output local feature map is

$$F_{conv} = Conv(X) \quad (4)$$

This step captures fine-grained local patterns like edges and textures.

3.2.2 Global Context Modelling via Self-Attention

The input is reshaped and projected into queries, keys, and values to compute global dependencies.

Reshape X into a sequence $X_{seq} \in R^{B \times N \times D}$, where $N = H \times W$.

Compute queries, keys and values using linear projections:

$$Q = X_{seq}W_Q, K = X_{seq}W_K, V = X_{seq}W_v \quad (5)$$

Calculate self-attention weights and global outfit F_{attn}.

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (6)$$

Reshape F_{attn} back to spatial dimensions $R^{B\times C\times H\times W}$.

3.2.3 Adaptive Gating Mechanism

An adaptive gate computes a dynamic weight parameter α to combine the convolutional and attention features based on local and global relevance. Compute gate coefficient using a small multi-layer perceptron or sigmoid activation over pooled features:

$$\alpha = \sigma\left(W_g[F_{conv}; F_{attn}] + b_g\right) \quad (7)$$

The parameter $\alpha \in [0,1]$ acts as a balancing factor for every spatial location or channel.

3.2.4 Feature Fusion and Final Output

The local convolutional features and global attention features are merged using the adaptive weight α.

Fuse the two feature representations:

$$F_{out} = \alpha . F_{conv} + (1-\alpha).F_{attn} \quad (8)$$

Pass F_{out} through feed-forward networks (FFN) and normalization layers for downstream tasks.

3.3. Modelling of WOA

The WOA is a nature-inspired meta-heuristic method that mimics the bubble-net hunting behaviour of humpback whales. The process involves initializing a random population of search agents, updating their positions through encircling, spiral bubble-net feeding, or random searching, and repeating these steps until a stopping condition is met. Flow chart of WOA for social media engagement classification is represented in figure 4.

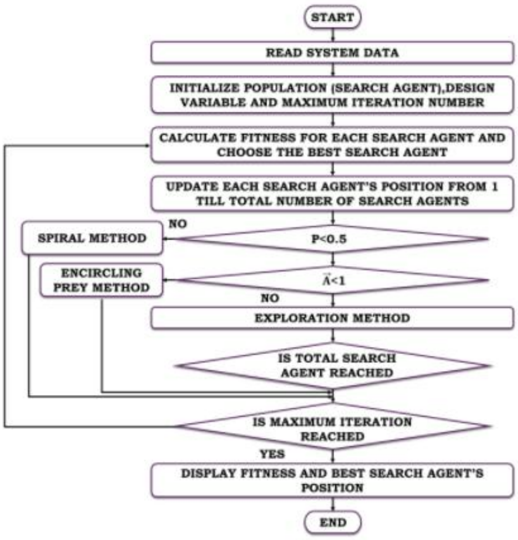

Figure 4: *Flowchart of WSO*

3.3.1 Initialization and Parameter Setup

Define the problem's search space lower and upper bounds, maximum number of iterations t_{Max}, and population size N and generate random positions for N search agents X_i within the boundaries:

$$X_i = lb + rand(0,1) \times (ub - lb) \quad (9)$$

Compute the objective/fitness function for each search agent and identify the best search agent, which is representing the prey.

3.3.2 Update Coefficient Vectors

At the start of each iteration, update the control parameters and coefficient vectors.

$$a = 2 - t\left(\frac{2}{t_{Max}}\right) \quad (10)$$

where a is a control parameter.

3.3.3 Choose Movement Strategy

Generate a random number $p \in [0,1]$ and check the magnitude of vector $\vec{A}$ to decide which behavior to simulate and Whales update their positions closer to the best agent.

$$X(t+1) = X^*(t) - \vec{A}.\vec{D} \quad (11)$$

Whales move in a helical/spiral path toward the prey:

$$X(t+1) = \vec{D}.e^{bl}.\cos(2\pi l) + X^*(t) \quad (12)$$

Whales update positions randomly based on a chosen random whale X_{rand} instead of the best whale:

$$X(t+1) = X_{rand} - \vec{A}.\vec{D}_{rand} \tag{13}$$

3.3.4 Boundary Check and Evaluation

Check limits: Ensure updated search agent positions stay within the defined problem boundaries ub and lb and compute the fitness of all updated whales. If any new whale has a better fitness value than X^*, update X^*.

3.3.5 Termination

Increment the iteration counter $t = t + 1$.Repeat Steps 3.3.2 through 3.3.4 until $t > t_{Max}$ .Output the final optimal solution X^* and its optimal fitness score.

4. Results and Discussion

The ACTN-WOA is proposed for social media engagement classification, which is evaluated using python software. The name of dataset used for simulation is Instagram analytics dataset and includes four classes, they are high, low, medium and viral.

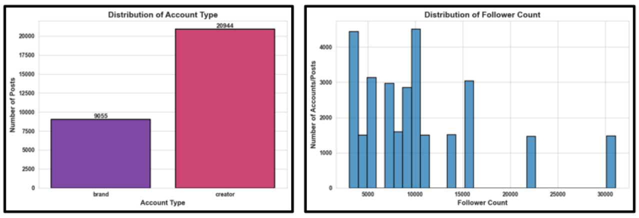

Figure 5: *Distribution of account type and distribution of follower count*

Figure 5 shows the distribution of account type and distribution of follower count. The left chart displays the Distribution of Account Type based on the total number of social media posts. It shows that brand accounts account for exactly 9,055 posts in the dataset. In contrast, creator accounts represent a much higher volume, total 30,944 posts. The right chart displays the Distribution of follower Count plotted against the number of accounts or posts. The follower counts data ranges widely across the horizontal x-axis, spanning from 0 up to 30,000 followers. The highest concentrations of accounts peak near the 4,500 counts frequency mark at multiple intervals. The isolated data bars appear further down the axis, specifically around the 22,500 and 30,000 follower marks.

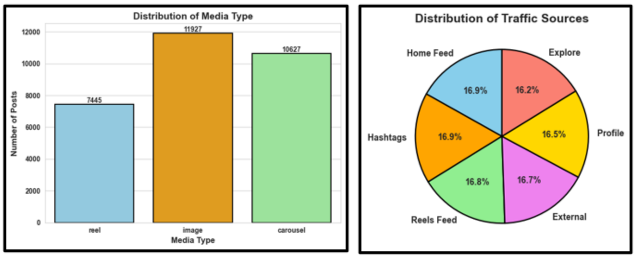

Figure 6: *Distribution of media type and distribution of traffic sources*

Figure 6 shows the distribution of media type and distribution of traffic sources. The bar chart on the left illustrates the distribution of media type, showing that images are the most frequent post type with 11,927 posts. Carousel posts follow as the second most common format, total 10,627 posts. Reels represent the lowest volume among the media types, accounting for 7,445 posts. On the right, the pie chart displays a highly balanced distribution of traffic sources" across six distinct channels. Home Feed and Hashtags contribute the highest individual shares, each driving exactly 16.9% of the traffic. Reels Feed closely follows at 16.8%, while External sources account for 16.7% of the distribution. Profile traffic brings in 16.5%, and the Explore page constitutes the smallest share at 16.2%.

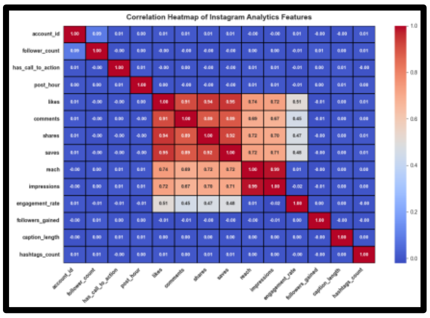

Figure 7: *Correlation heatmap*

Figure 7 shows the correlation heatmap, which illustrates the relationships between various Instagram analytics features, where values closer to 1.00 represent stronger positive relationships. The diagonal red line displays a perfect correlation of 1.00 as each metric is compared against itself. Strong positive correlations exist among primary engagement metrics, such as likes and shares at 0.94, and likes and saves at 0.93. Visibility metrics are also tightly linked to engagement, with reach having a 0.74 correlation with likes and impressions showing a 0.82 correlation with reach.

Table 1: *Classification report*

Classes	Precision	Recall	F1-Score	support
High	0.8609	0.8460	0.8534	1500
Low	0.9317	0.9100	0.9207	1500
Medium	0.8778	0.8427	0.8599	1500
Viral	0.8890	0.9607	0.9234	1500
Accuracy			0.8898	6000
Macro avg	0.8898	0.8898	0.8894	6000
Weighted avg	0.8898	0.8898	0.8894	6000

Table 1 shows the classification report, which includes four classes, they are high, low, medium and viral. The precision of class high is 0.8609, low is 0.9317, medium is 0.8778 and viral is 0.8890. The recall of class high is 0.8460, low is 0.9100, medium is 0.8427 and viral is 0.9607. The F1-Score of class high is 0.8534, low is 0.9207, medium is 0.8599 and viral is 0.9234. The classification report shows the accuracy of proposed ACTN-WSO is 88%.

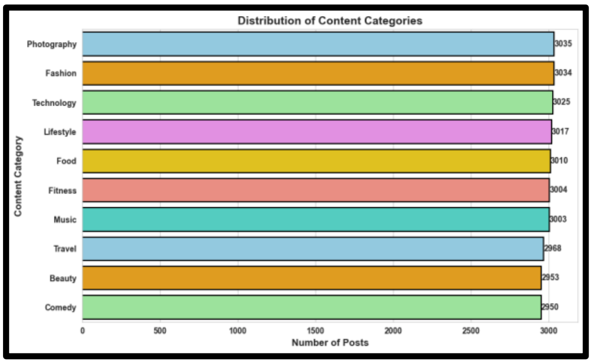

Figure 8: *Distribution of content categories*

Distribution of content categories is shown in figure 8. The categories analyzed include Photography, Fashion, Technology, Lifestyle, Food, Fitness, Music, Travel, Beauty, and Comedy. Photography holds the highest volume with 3,035 posts, closely followed by Fashion at 3,034 and Technology at 3,025. Conversely, Comedy represents the smallest category in the data set, accounting for 2,950 total posts.

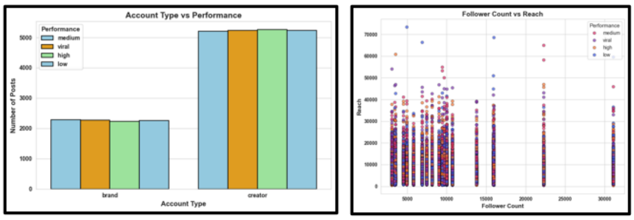

Figure 9: *Account type vs performance and Follower count vs racks*

Figure 9 shows the account type vs performance and follower count vs racks. The first chart, a bar graph titled account type vs performance, shows that creator accounts post significantly more content than brand accounts, with creator accounts generating over 5,000 post per performance category compared to brand accounts which consistently hover around 2,300 posts per category. The second chart, a scatter plot titled follower count vs reach, displays data points clustered mostly between 0 and 15,000 followers, with a few accounts extending up to 30,000 followers. The reach for most of these posts remains concentrated below 40,000, though a small number of exceptional high and viral posts spike to a peak reach between 60,000 and 73,000.

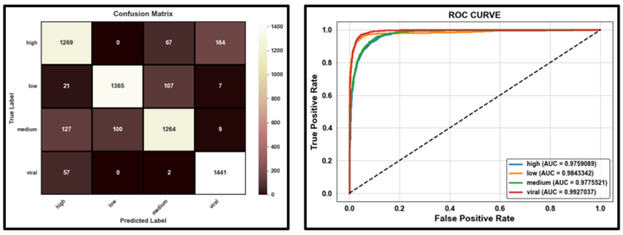

Figure 10: *Confusion matrix and ROC Curve*

Figure 10 shows the confusion matrix and ROC curve. The confusion matrix demonstrates strong diagonal performance, correctly identifying 1,269 high, 1,360 low, 1,264 medium, and 1,441 viral instances. Minor errors are visible, such as 164 true high cases being misclassified as viral and 127 true medium cases misclassified as high. Complementing this, the ROC curves display excellent predictive accuracy, yielding high AUC values of 0.9759 for high, 0.9843 for low, and 0.9776 for medium. The viral category achieves the highest overall discriminative performance with an exceptional AUC score of 0.9927, confirming the robust reliability of the model.

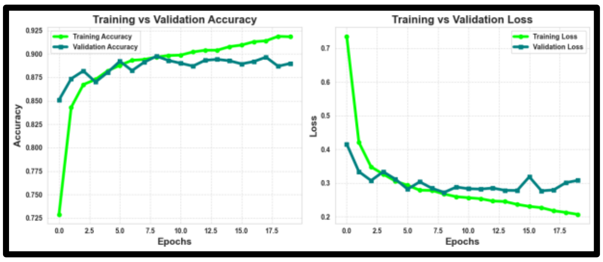

Figure 11: *Accuracy and loss of proposed ACTN-WOA*

The accuracy and loss of proposed ACTN-WOA are represented in figure 11. The accuracy of proposed ACTN-WOA is 88% and the loss of proposed ACTN-WOA is 20%, which demonstrates the effectiveness of proposed system.

Table 2: *Comparison of response time*

Method	Response time
AGCRN-T-WSO [8]	0.7s
DNN-FM [9]	0.6s
GAN-GNN [10]	0.5s
Proposed ACTN-WOA	0.2s

Table 2 shows the comparison of response time. The response time of proposed ACTN-WOA is 0.2s. Lower response time (faster inference latency) in an ACTN-WOA classification model enables real-time edge deployment, reduced compute costs, and instant decision-making.

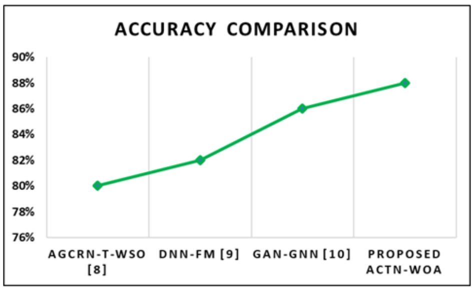

Figure 12: *Accuracy Comparison*

Figure 12 shows the accuracy comparison. The accuracy of proposed ACTN-WOA is 88%. High accuracy in an ACTN-WOA for social media engagement classification ensures precise predictions of user likes and shares. It reduces false results, targets the right audience, spots viral trends early, and improves content recommendations by understanding complex user Behavior patterns.

5. Conclusion

In this paper, a hybrid ACTN-WOA has been proposed for social media engagement classification. The performance analysis is carried out using python software. ACTN-WOA are effective at classifying social media engagement, achieving 88% accuracy. Utilizing optimized feature sets allows for efficient, real-time detection without requiring massive, computationally expensive models. The developed method is compared with existing methods AGCRN-T-WSO, DNN-FM and GAN-GNN in terms of precision, recall and F1-Score. The DL models, ACTN-WOA offer high accuracy of 88%, and less computational time of 0.2s in social media engagement classification. Future work in social media engagement classification focuses on moving past simple likes and comments to capture passive actions like saves and video-watches and advanced AI models to study micro-behaviors, cross-platform data, and hidden community networks for better content personalization and brand return on investment.

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