

Exploring Human-Computer Interaction Through Behaviour Analysis Using Artificial Intelligence with Metaheuristic Strategies for Enhanced User Experience

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Abstract—The analysis of human-computer interaction (HCI) for mobile devices is a comparatively new research area, which is financially effective and is accessible for a year. Developments in mobile technologies have influenced significant changes in how and when individuals access and utilize data, and are having a penetrating influence on how users handle their routine data requirements. Artificial intelligence (AI) methods have increased quickly in the past years in terms of calculating with smart mobile phones, which normally permit devices to function intelligently. Standard AI methods consist of natural language processing (NLP), deep learning (DL), and machine learning (ML) techniques, in addition to expert systems and knowledge representation, which are applied to create more efficient targeted mobile applications. This study proposes an Enhancing Human-Computer Interaction through Mobile User Behavior Analysis with Artificial Intelligence and Metaheuristic Strategies (HCIMUBA-AIMS) technique. The proposed HCIMUBA-AIMS technique aims to develop an accurate and effective model for analyzing user behaviour in mobile applications using state-of-the-art models. Primarily, the data normalization stage utilizes the linear scaling normalization (LSN) method for pre-processing. For the selection of the feature processing, the improved grey wolf optimizer (IGWO) method is employed. Moreover, the proposed HCIMUBA-AIMS technique executes a hybrid of convolutional neural network, bidirectional long short-term memory with spatiotemporal attention mechanism (CNN-BiLSTM-STA) technique for the process of classification. Ultimately, the horse herd optimization algorithm (HHOA) fine-tunes the hyperparameter values of the CNN-BiLSTM-STA technique optimally and results in better classification. The efficiency of the HCIMUBA-AIMS method is validated under a benchmark dataset. The validation of the HCIMUBA-AIMS method illustrated improved performance over existing techniques.

Keywords—Human-computer interaction; user behavior analysis; mobile applications; Artificial Intelligence; metaheuristic strategies

I. INTRODUCTION

Human society exists through communication between its entities and their settings. In day-to-day life communicate with other individuals and objects to accomplish a kind of action that is significant to us. Computerized machines and computers are

a novel element. They progressively influence various aspects of daily life, such as how actions are performed, interactions occur, and communication happens with the surroundings. An innovative concept of communication emerged as HCI [1]. While the computers itself have highly advanced, the general HCI still involves simple mechanical gadgets - keyboards, mice, and joysticks – which highly decrease the naturalness and effectiveness of such communication. Recent investigations have shown it is entirely normal to point at virtual space utilizing the index finger and to discover virtual objects employing one's hands. It is also easier to get to know other people in a similar virtual setting while seeing them manipulate objects in it [2]. Smart gadgets like Android phones bring us existing mobile access to the internet and also make mobile internet utilization quickly every day by raising the popularity of user behavior. It has become significant for internet service providers to accomplish the diverse challenges, namely management of the network, planning the network, and planning the capacity and system resources [3].

The user behavior of mobile is inspected by diverse significant features like mobility patterns, utilization of applications, and data. Data usage is essential and it is generally relevant to the users, mobile gadgets, and diverse applications also the kind of system access is both 2G and 3G. Afterward, controlling the urban mobility method deals with conflicting interests: employees and visitors want to improve mobility whereas the similar time municipalities or road authorities want to decrease traffic to upgrade availability and lessen pollution [4]. While application usage is the other significant feature in the user behavior to know the consumption of network resources. Recently, AI models have been developed quickly in the framework of computing with smart mobile devices, which generally enables the gadgets to function in an intelligent way. AI is implemented for several kinds of mobile data, namely unstructured, structured, and semi-structured. Well-known AI models comprising DL and ML, together with expert systems and knowledge representation, might be employed based on their data features to make the target mobile applications intelligent [5].

This study proposes an Enhancing Human-Computer Interaction through Mobile User Behavior Analysis with Artificial Intelligence and Metaheuristic Strategies (HCIMUBA-AIMS) technique. The proposed HCIMUBA-AIMS technique aims to develop an accurate and effective model for analyzing user behaviour in mobile applications using state-of-the-art models. Primarily, the data normalization stage utilizes the linear scaling normalization (LSN) method for pre-processing. For the selection of the feature processing, the improved grey wolf optimizer (IGWO) method is employed. Moreover, the proposed HCIMUBA-AIMS technique executes a hybrid of convolutional neural network, bidirectional long short-term memory with spatiotemporal attention mechanism (CNN-BiLSTM-STA) technique for classification. Ultimately, the horse herd optimization algorithm (HHOA) fine-tunes the hyperparameter values of the CNN-BiLSTM-STA technique optimally and results in better classification. The efficiency of the HCIMUBA-AIMS method is validated under a benchmark dataset.

II. LITERATURE SURVEY

Wang et al. [6] introduce a wide-ranging analysis of the metaverse to tackle the gap in the current novel where there is an absence of study which assess the group of metaverse and building blocks from human-centric perception. This method synthesizes an explanation of the metaverse from current literature and defines key resources. It presents a detailed structure including the nature of the metaverse, input or output technologies that assist multi-sensory HCI, together with applications across different fields. Antonio et al. [7] recognize the drivers of user adoption of mobile P2P payments and advance ML for forecasting the utilization of this thriving payment option. Zhao et al. [8] intend to project an AI entertainment robot, which can offer a higher-quality UX. CNN is employed for feature extraction. Afterward, a robot control and hand-eye method is used. Deng et al. [9] developed an innovative privacy-preserving method in an edge user behavioral study named Safe-FL for safeguarding the behavioral confidentiality of each edge participant by presenting encryption and secure data aggregation in the structure of FL. This method builds an FL-based edge user behavior analysis structure. Then, a hybrid encryption method is employed to encode the local model hierarchically for safeguarding gradient privacy in edge user behavior analysis and to decrease the encryption computation overhead. Finally, to enhance the robustness of the method, a decentralized gradient aggregation model depending on a blockchain is presented. In [10], a product design optimization model and user behavior data analysis reliant on an enhanced CNN are constructed and studied. Initially, it employs NN for removing user behavior aspects and attaining satisfaction and corresponding attention over an emotional analysis of behavior. Li et al. [11] proposed a multi-scale hierarchical GAN (MSH-GAN) comprising a multi-class discriminator and multiple generators. Furthermore, the traffic utilization behavior of diverse consumers shows robust clustering features. Afterward, the gap between macro-scale user clusters and micro-scale behavior patterns is connected by presenting the switch mode generators. Murrar et al. [12] presented a technology adoption method for AI-powered mobile apps by ranging the VAM to comprise customer trust. A

sampling method guaranteed a typical instance of customers. This study employed a validated device to assess the perceived value of customers, adoption intention, and trust.

III. MATERIALS AND METHODS

In this study, the HCIMUBA-AIMS method is presented. The aim of the HCIMUBA-AIMS method is to develop an accurate and effective model for analyzing user behavior in mobile applications using state-of-the-art models. Fig. 1 depicts the flow of the HCIMUBA-AIMS technique.

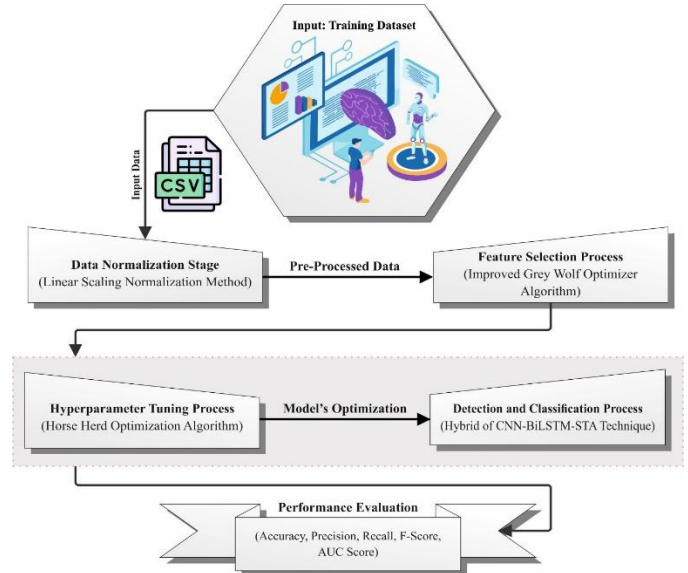


Fig. 1. Workflow of the HCIMUBA-AIMS method.

A. Data Normalization

Initially, the LSN method is used to convert input data into a valid format. LSN is an extensively applied model in mobile user behavior studies for HCI to guarantee that data values are converted into a constant range, normally between (0,1) or (-1,1). This method assists in processing variations in user behavior data, like navigation patterns, screen interaction times, and touch gestures, by making them comparable across several devices and users. By using linear scaling, high values are fine-tuned while preserving the comparable relationship among data points, resulting in enhanced precision in AI-driven studies. It further improves the performance of ML methods by avoiding bias due to larger numeric variance. In mobile applications, it plays an important role in processing behavioral insights and enhancing personalized user experiences. Furthermore, it helps in enhancing meta-heuristic methods, guaranteeing effective convergence in anomaly detection and behavior prediction.

B. IGWO-Driven Feature Selection Strategy

In feature selection, the IGWO [13] approach has been employed. The GWO is motivated by the collaborative searching behavior of grey wolf packs. It mimics the cooperative mechanisms observed in wolf packs to resolve optimization problems. It is represented by a constant framework and needs some parameters to be fine-tuned. In GWO, grey wolves hold 4 social ranks in descending order of rank: alpha (α), beta (β), delta (δ), and omega (ω) wolves. Initially, 3 wolf classes

manage the omega wolf in searching for prey. The mathematical expression for neighboring prey:

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (2)$$

Now, t implies the iteration counts; $\vec{D}$ specifies the distance between wolf and prey; $\vec{A}$ and $\vec{C}$ the vector coefficient; $\vec{X}_p$ and $\vec{X}$ implies the position vectors of the wolf and prey, respectively. $\vec{A}$ and $\vec{C}$ vectors were expressed below:

$$\vec{A} = 2 \cdot a \cdot \vec{r}_1 - a \quad (3)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (4)$$

Now, r_1 and r_2 implies arbitrary values between zero and one; the convergence factor a take values in the range $[0,2]$ and reduce linearly as the iteration counts rise.

The initial population in the grey wolf optimizer is created arbitrarily. If the initial population generation is highly focused, it will impact the outcome of the solution method. Furthermore, the GWO also faces the problem of premature convergence. To handle these 2 points, an enhanced GWO is proposed in this study.

1) *Generating initial population using tent mapping*: The fundamental GWO was unable to guarantee that the initial population is consistently distributed in the solution area. Chaotic sequences offer benefits of randomness, ergodicity, and regularity. Compared with other mappings, tent mapping produces a more uniform sequence. Consequently, this study employs the tent mapping for initializing the population of grey wolves. The tent mapping might be stated:

$$x_{t+1} = \begin{cases} \frac{x_t}{u} & 0 \leq x_t < u \\ \frac{1-x_t}{1-u} & u \leq x_t \leq 1 \end{cases} \quad (5)$$

Here, the sequence of distribution is more uniform if u is taken as 0.5, and it comprises the most common tent mapping, once the distribution density is insensitive to modifying parameters. Then Eq. (5) might be changed into Eq. (6).

$$x_{t+1} = \begin{cases} 2x_t & 0 \leq x_t < 0.5 \\ 2(1-x_t) & 0.5 \leq x_t \leq 1 \end{cases} \quad (6)$$

$$Y = Y_{\min} + x_t \cdot (Y_{\max} - Y_{\min}) \quad (7)$$

2) *Improved convergence factor*: The convergence factor impacts the searching ability of GWO. It utilizes a linear convergence factor, but the process of convergence in most optimization problems is non-linear. Consequently, this study presents an exponential function to enhance the convergence factor a .

$$a = 2 - \frac{2(e^{\frac{t}{T}} - 1)}{e - 1} \quad (8)$$

Here, T specifies the maximum number of iterations.

The fitness function (FF) balances classification precision and the count of chosen attributes to maximize performance and minimize feature set dimension.

$$Fitness = \alpha * ErrorRate + (1 - \alpha) * \frac{\#SF}{\#All_F} \quad (9)$$

Now, *ErrorRate* symbolizes the classifier error rate with the labeled attributes. *ErrorRate* is determined as the proportion of incorrect classifiers to the number of classifiers completed, specified as a value between (0,1). *#SF* refers to the chosen attribute counts and *#All_F* signifies overall feature amounts in the original data set. α was used for controlling the importance of classifier quality as well as subset length.

C. Hybrid Classification Model

Moreover, the proposed HCIMUBA-AIMS technique executes a hybrid CNN-BiLSTM-STA technique for classifying processes. The CNNs as the initial stage of the presented method to remove spatial data from the input source. Primarily, dual CNN [14] layers carry out convolutional processes.

$$z_{i,j,k} = \sigma \left(\sum_{m,n} x_{m,n} \cdot w_{i,j,m,n} + b_k \right) \quad (10)$$

Whereas, $x_{m,n}$ characterizes the values of input pixels with respect to the local receptive area, $w_{i,j,m,n}$ signifies the weights, b_k characterizes the bias, and σ represents the activation function. The SAM especially concentrates on important geographic regions and temporal intervals inside the input data. The SAM of this study contains two basic elements. Firstly, a convolutional layer can be applied to all frames to make spatial attention valuations as shown:

$$SA_t = \sigma(Conv2D(x_t, W_s) + b_s) \quad (11)$$

Whereas, SA_t denote the score of the spatial attention for time-step t , W_s and b_s represent trainable convolution weights and bias. A dense layer is then used to compute temporal attention by aggregating spatial attention values to evaluate the contribution of all time steps.

$$TA_t = \sigma(Dense(Flatten(S_t), W_t) + b_t) \quad (12)$$

Here, TA_t refers to the temporal attention score for time-step t , W_t and b_t symbolizes trainable dense layer weighting and bias. Afterward, the attention scores of the temporal and spatial are incorporated as:

$$CA_t = SA_t \odot TA_t \quad (13)$$

Now, $\odot$ stands for the Hadamard product, and CA_t characterizes the joined attention score for time step t . Afterward, the presented model uses the third CNN layer, which examines the learned incorporated attention mapping to improve the feature representations.

$$z'_{i,j,k} = \sigma \left(\sum_{m,n} z_{m,n} \cdot w'_{i,j,m,n} + b'_k \right) \quad (14)$$

Whereas, $z_{m,n}$ implies the input, while $w'_{i,j,m,n}$, b'_k , and σ represents convolutional, bias, and activation. The 3rd

convolutional representation process is important as it improves the spatio-temporal using attention module.

$$\bar{y}_i = LSTM(a_i, \bar{y}_{i-1}) \quad (15)$$

$$\bar{y}_i = LSTM(a_i, \bar{y}_{i-1}) \quad (16)$$

$$y_i = [\bar{y}_i, \bar{y}_i] \quad (17)$$

Here, $\bar{y}_i$ and $\bar{y}_i$ denotes reverse and forward hidden layers, correspondingly, and y_i implies the connection. After handling the data sequence through the initial Bi-LSTM layer, the method applies layer normalization to alleviate the threats of exploding or vanishing gradients throughout training. Following layer normalization, the information flows into the next Bi-LSTM layer to explain more complex patterns and relationships within the data. Therefore, the stacked Bi-LSTM layers compress temporal dynamics to improve predictive features. At last, the decoding layer converts the output from the Bi-LSTM layers into the essential spatio-temporal data for prediction process.

$$Prediction = Reshape(Dense(y_i, W_o) + b_o) \quad (18)$$

Whereas the parameter b_o denotes the bias term, W_o signifies the weights of the last layer and. Fig. 2 portrays the architecture of CNN-BiLSTM-STA.

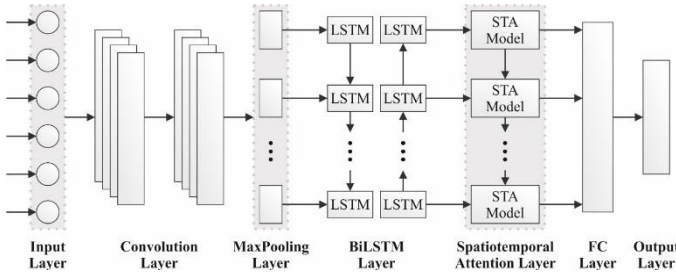


Fig. 2. Architecture of CNN-BiLSTM-STA technique.

D. Parameter Optimizer Using HHOA

Ultimately, the HHOA [15] fine-tunes the hyperparameter values of the CNN-BiLSTM-STA technique optimally and results in a better classifier model. HHOA is concentrated on horses' natural behavioral trends. The most standard behavioral forms identified consist of imitation (I), defense (D), sociability (S), grazing (G) mechanism, roaming (R), and hierarchy (H). The horses are separated into 4 age-based groups: W , X , Y , and Z . The horses are at the ages of 0-5 at the Z -class, Y , and X groups are among the age groups of 5-10 and 10-15, individually. While every horses more than 15 years takes part in the W -class. As with many wider herd animals, determining a steady method of "pecking order" or hierarchy is important to reduce fostering, violent behavior and social unity. The HHOA mechanism is illustrated through the succeeding velocity and position vectors.

$$P_i^{n,age} = y_i^{n,age} + P_i^{(n-1),age}, age = W, X, Y, Z \quad (19)$$

Whereas, n refers to iterative numbers, $(P_i^{n,age})$ denote the present location of i^{th} horse, $(v_i^{n,age})$ stands for the velocity vector of i^{th} horse, and age displays the variety of each horse.

$$\bar{V}_i^{n,W} = \bar{G}_i^{n,W} + \bar{D}_i^{n,W} \quad (20)$$

$$\bar{V}_i^{n,X} = \bar{G}_i^{n,X} + \bar{S}_i^{n,X} + \bar{H}_i^{n,X} + \bar{D}_i^{n,X} \quad (21)$$

$$\bar{V}_i^{n,Y} = \bar{G}_i^{n,Y} + \bar{S}_i^{n,Y} + \bar{H}_i^{n,Y} + \bar{D}_i^{n,Y} + \bar{I}_i^{n,Y} + \bar{R}_i^{n,Y} \quad (22)$$

$$\bar{V}_i^{n,Z} = \bar{G}_i^{n,Z} + \bar{I}_i^{n,Z} + \bar{R}_i^{n,Z} \quad (23)$$

The matrix of response is applied for arranging the herd's horses from best to poor place according to their scores of fitness after all cycles. The major 6 stages of social behavior for the HHOA can be handled within the following subdivisions.

1) *Grazing (G)*: Horses consume additional food as well as grasses and plants. Daily horses spend 16 to 20 hours feeding on grass, with very little time for relaxation.

$$\bar{G}_i^{n,age} = \bar{g}_i^{n,age}(u + \wp l)[P_i^{n-1}], age = W, X, Y, Z \quad (24)$$

$$\bar{g}_i^{n,age} = \bar{g}_i^{(n-1),age} \times \omega_g \quad (25)$$

Here, $\bar{P}_i^{n,age}$ refers to the grazing motion variable of the horse. This variable is decreased linearly by $\omega_g \cdot u$ and 1 represent the lower and upper grazing field limits, respectively. $\wp$ stands for randomly generated variable among (0, 1). Recommends that the best values for these limits are 1.05 and 0.95, individually. P signifies randomly generated numbers. Moreover, it is noted that g variable has an initial value of 1.5 for each age group.

2) *Sociability (S)*: In the behavior of horses, the HHOA is additionally valued the sociability and it is one regular habit between the ages of 5 and 15.

$$\bar{S}_i^{n,age} = s_i^{n,age} \left[\left(\frac{1}{N} \sum_{m=1}^N P_m^{n-1} \right) - P_i^{n-1} \right], age = X, Y \quad (26)$$

$$\bar{s}_i^{n,age} = \bar{s}_i^{(n-1),age} \times \omega_s \quad (27)$$

Here, N means total horse counts, ω_s represents the sociability reduction coefficient, $(\bar{S}_i^{n,age})$ refers to the horse in doubt, n^{th} iteration approaches the flock, and $(\bar{s}_i^{n,age})$ denotes the social movement of the i^{th} horse.

3) *Hierarchy (H)*: Horses remains the prevailing sentiment animals. A more experienced and dominant horse within the group is typically followed by other horses. The movement of the herd's horse follows the dominant horse and was measured by the variable h .

$$\bar{H}_i^{n,age} = \bar{h}_i^{n,age}[P_i^{n-1} - P_i^{n-1}], age = X, Y \quad (28)$$

$$\bar{h}_i^{n,age} = \bar{h}_i^{(n-1),age} \times \omega_h \quad (29)$$

Now, $(\bar{H}_i^{n,age})$ characterizes the horse's location. The best horse position was presented by $(\bar{P}_i^{n-1})$. The hierarchy decrease coefficient can be represented as ω_h .

4) *Defense (D)*: Horses' reactions establish that they experienced hunting. They show a fight-or-flight reaction for their defense. Horses contest for water and food in a try to defeat their competitors and avoid dangerous zones and hunters. The horse's defensive mechanism is signified by the

negative parameter d that has animals apart from poor locations.

$$\vec{D}_i^{n,age} = -\vec{d}_i^{n,age} \left[\left(\frac{1}{\beta N} \sum_{m=1}^N P_m^{n-1} \right) - P_i^{n-1} \right], age$$

$$= W, X, Y \quad (30)$$

$$\vec{d}_i^{n,age} = \vec{d}_i^{(n-1),age} \times \omega_d \quad (31)$$

Whereas, $\vec{D}_i^{n,age}$ age embodies the i^{th} escaping vector of horse. The horse count by the poorest positions is specified by βN . In contrast, β is considered as 20% of the horses. The defense-reducing feature is presented by ω_d .

5) *Imitation (I)*: Generally, the fresh horses within the flock focused on the old ones by observing and copying them. As they grow old, younger horses even have to imitate other horses. Now, imitation behavior is characterized by parameter i .

$$\vec{I}_i^{n,age} = \vec{I}_i^{n,age} \left[\left(\frac{1}{\gamma N} \sum_{m=1}^N \hat{P}_m^{n-1} \right) - P_i^{n-1} \right], age = Y, Z \quad (32)$$

$$\vec{I}_i^{n,age} = \vec{I}_i^{(n-1),age} \times \omega_i \quad (33)$$

Here, the i^{th} imitation movement vector, $\hat{A}$, was signified by $(\vec{I}_i^{n,age})$. The horse counts in the best location are specified by γN . The coefficient of imitation reduction was presented by ω_i .

6) *Roaming (R)*: Horses frequently pasture and move around among grasslands looking for food. A horse may quickly choose to graze at another place. They journey through dissimilar places frequently, searching for new grass and learning about their surroundings. Once horses are young, this behavior is frequently present, however, it frequently becomes invisible as they become older. The wandering signal is signified by r .

$$\vec{R}_i^{n,age} = \vec{r}_i^{n,age} [\wp P_i^{n-1}], age = Y, Z \quad (34)$$

$$\vec{r}_i^{n,age} = \vec{r}_i^{(n-1),age} \times \omega_r \quad (35)$$

Now, ω_r characterizes the imitation reduction coefficient and $(\vec{R}_i^{n,age})$, represents the i^{th} random velocity vector of the horse. At the ages Y and Z , it is recommended to assign the value r to 0.05 and 0.1, correspondingly.

$$\vec{V}_i^{n,W} = [\vec{g}_i^{n,W}(u + \wp l)[P_i^{n-1}]]$$

$$- \left[\vec{d}_i^{n,W} \left[\left(\frac{1}{\beta N} \sum_{m=1}^N P_m^{n-1} \right) - P_i^{n-1} \right] \right] \quad (36)$$

$$\vec{V}_i^{n,X} = [\vec{g}_i^{n,X}(u + \wp l)[P_i^{n-1}]] - \left[\vec{g}_i^{n,X} \left[\left(\frac{1}{N} \sum_{m=1}^N P_m^{n-1} \right) - P_i^{n-1} \right] \right]$$

$$+ [\vec{h}_i^{n,X}[P_i^{n-1} - P_i^{n-1}]] - \left[\vec{d}_i^{n,X} \left[\left(\frac{1}{\beta N} \sum_{m=1}^N P_m^{n-1} \right) - P_i^{n-1} \right] \right] \quad (37)$$

$$\vec{V}_i^{n,Y} = [\vec{g}_i^{n,Y}(u + \wp l)[P_i^{n-1}]] - \left[\vec{g}_i^{n,Y} \left[\left(\frac{1}{N} \sum_{m=1}^N P_m^{n-1} \right) - P_i^{n-1} \right] \right] + [\vec{h}_i^{n,Y}[P_i^{n-1} - P_i^{n-1}]]$$

$$- \left[\vec{d}_i^{n,Y} \left[\left(\frac{1}{\beta N} \sum_{m=1}^N P_m^{n-1} \right) - P_i^{n-1} \right] \right] + \left[\vec{g}_i^{n,Y} \left[\left(\frac{1}{\gamma N} \sum_{m=1}^N \hat{P}_m^{n-1} \right) - P_i^{n-1} \right] \right] + [\vec{h}_i^{n,Y}(\wp P_i^{n-1})] \quad (38)$$

$$\vec{V}_i^{n,Z} = [\vec{g}_i^{n,Z}(u + \wp l)[P_i^{n-1}]] - \left[\vec{g}_i^{n,Z} \left[\left(\frac{1}{\gamma N} \sum_{m=1}^N \hat{P}_m^{n-1} \right) - P_i^{n-1} \right] \right]$$

$$+ [\vec{h}_i^{n,Z}(\wp P_i^{n-1})] \quad (39)$$

Fitness selection is a key factor influencing HHOA efficiency. The hyperparameter selection process encodes solutions to compute candidate performance, using accuracy as the main criterion in the defined fitness function.

$$Fitness = \max(P) \quad (40)$$

$$P = \frac{TP}{TP + FP} \quad (41)$$

Now, the term TP and FP portray the positive values of true and false correspondingly.

IV. EXPERIMENTAL VALIDATION

The performance validation of the HCIMUBA-AIMS method is performed under the mobile device usage and user behavior dataset [16]. The dataset encompasses 700 instances across five class labels, with 9 out of 10 features selected for analysis, as shown in Table I.

TABLE I. DATASET DESCRIPTION

Class Labels	Sample Numbers
User Behaviour Level-1	136
User Behaviour Level-2	146
User Behaviour Level-3	143
User Behaviour Level-4	139
User Behaviour Level-5	136
Total Samples	700

Fig. 3 presents the confusion matrices of the HCIMUBA-AIMS approach under 80:20 and 70:30 of TRAPHA /TESPHA. The consequences state that the HCIMUBA-AIMS method has effectual recognition and classification of entire five classes.

Table II and Fig. 4 embody the user behavior analysis of the HCIMUBA-AIMS method under 80:20 and 70:30 of TRAPHA/TESPHA. With 80%TRAPHA, the HCIMUBA-AIMS technique gives average $accuracy$, $precis_n$, $recal_l$, F_{score} , and AUC_{score} of 95.71%, 89.48%, 89.40%, 89.42%, and 93.36%, correspondingly. Furthermore, based on 20%TESPHA, the HCIMUBA-AIMS method delivers average $accuracy$, average $precis_n$, $recal_l$, F_{score} , and AUC_{score} of 95.14%, 87.75%, 88.01%, 87.71%, and 92.49%, correspondingly. Moreover, depending upon 70%TRAPHA, the HCIMUBA-AIMS model offers an average $accuracy$, $precis_n$, $recal_l$, F_{score} , and AUC_{score} of 93.80%, 84.73%, 84.48%, 84.49%, and 90.30%, correspondingly. At last, depending upon 30%TESPHA, the HCIMUBA-AIMS model obtains an average $accuracy$, $precis_n$,

$recall$, F_{score} , and AUC_{score} of 94.48%, 86.52%, 85.91%, 85.98%, and 91.23%, correspondingly.

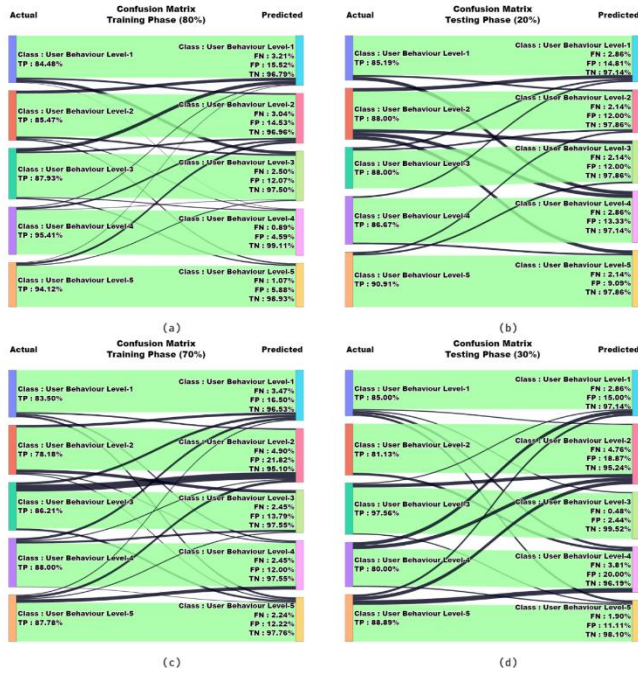


Fig. 3. Confusion matrices of (a-b) TRAP of 80% and 70% and (b-d) TESP of 20% and 30%.

TABLE II. USER BEHAVIOR ANALYSIS OF HCIMUBA-AIMS MODEL AT 80:20 AND 70:30 OF TRAPHA/TEPHA

Class Labels	$Accu_r$	$Preci_n$	$Recal_l$	F_{score}	AUC_{score}
TRAPHA (80%)					
User Behaviour Level-1	94.64	84.48	89.09	86.73	92.55
User Behaviour Level-2	94.11	85.47	86.21	85.84	91.19
User Behaviour Level-3	94.46	87.93	85.71	86.81	91.27
User Behaviour Level-4	97.86	95.41	93.69	94.55	96.29
User Behaviour Level-5	97.50	94.12	92.31	93.20	95.50
Average	95.71	89.48	89.40	89.42	93.36
TEPHA (20%)					
User Behaviour Level-1	95.00	85.19	88.46	86.79	92.48
User Behaviour Level-2	92.14	88.00	73.33	80.00	85.30
User Behaviour Level-3	96.43	88.00	91.67	89.80	94.54
User Behaviour Level-4	95.71	86.67	92.86	89.66	94.64
User Behaviour Level-5	96.43	90.91	93.75	92.31	95.49
Average	95.14	87.75	88.01	87.71	92.49
TRAPHA (70%)					
User Behaviour Level-1	94.49	83.50	89.58	86.43	92.63
User Behaviour Level-2	92.04	78.18	85.15	81.52	89.49

User Behaviour Level-3	92.86	86.21	76.53	81.08	86.73
User Behaviour Level-4	95.10	88.00	88.00	88.00	92.46
User Behaviour Level-5	94.49	87.78	83.16	85.41	90.19
Average	93.80	84.73	84.48	84.49	90.30
TESPHA (30%)					
User Behaviour Level-1	94.29	85.00	85.00	85.00	90.74
User Behaviour Level-2	94.29	81.13	95.56	87.76	94.75
User Behaviour Level-3	97.14	97.56	88.89	93.02	94.14
User Behaviour Level-4	92.86	80.00	82.05	81.01	88.69
User Behaviour Level-5	93.81	88.89	78.05	83.12	87.84
Average	94.48	86.52	85.91	85.98	91.23

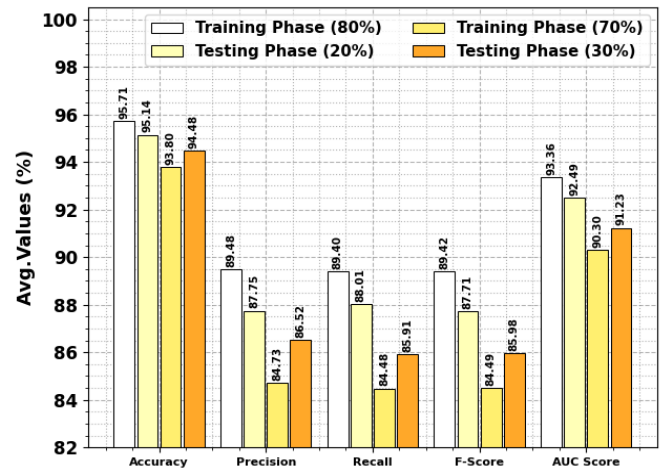


Fig. 4. Average of the HCIMUBA-AIMS model.

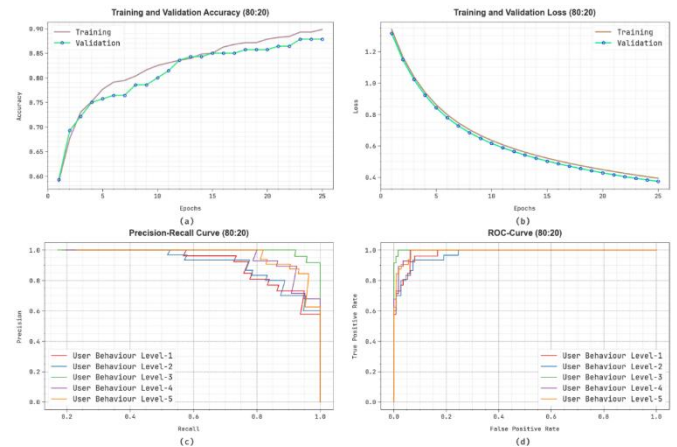


Fig. 5. HCIMUBA-AIMS model (a-b) accuracy/loss, and (c-d) PR/ROC curves on 80:20.

Fig. 4 establishes the classifier outcomes of the HCIMUBA-AIMS approach on 80:20. Fig. 5(a) determines the accuracy analysis of the HCIMUBA-AIMS technique. The figure shows that the proposed system attains increasing values over increasing epochs. Then, Fig. 5(b) exemplifies the loss of the

HCIMUBA-AIMS technique. The result indicates that the HCIMUBA-AIMS technique reaches lower values of training and validation loss. Fig. 5(c) presents the PR study of the HCIMUBA-AIMS technique. The outcomes indicate that the proposed technique results in increased PR values. Lastly, Fig. 5(d) illustrates the investigation of the ROC of the HCIMUBA-AIMS technique.

Table III and Fig. 6 [17] show the comparative study of the HCIMUBA-AIMS model with existing models. Based on *accu_r*, the HCIMUBA-AIMS model has achieved a higher *accu_r* of 95.71%, while the existing approaches like LDA, extra trees (ET), ridge classifier (RC), DRP-ARIMA, C3P-SMART, isolation forest (IF), and local outlier factor (LOF) have gained lower *accu_r* of 88.38%, 87.32%, 90.97%, 93.39%, 90.06%, 90.09%, and 89.48%, respectively. In addition, based on *preci_n*, the HCIMUBA-AIMS technique has achieved greater *preci_n* of 89.48%, whereas the existing models such as the LDA Model, ET, RC, DRP-ARIMA, C3P-SMART, IF, and LOF have got lower *preci_n* of 80.45%, 79.99%, 76.52%, 85.51%, 80.50%, 83.09%, and 84.41%, respectively. Also, based on *F_{score}*, the HCIMUBA-AIMS model has obtained a larger *F_{score}* of 89.42%, while the existing models, namely LDA Model, ET, RC, DRP-ARIMA, C3P-SMART, IF, and LOF have acquired lower *F_{score}* of 81.21%, 79.08%, 86.04%, 86.34%, 89.03%, 75.57%, and 77.85%, correspondingly.

TABLE III. COMPARISON STUDY OF HCIMUBA-AIMS APPROACH WITH EXISTING METHODS

Approach	<i>Accu_r</i>	<i>Preci_n</i>	<i>Recal_i</i>	<i>F_{score}</i>
LDA Model	88.38	80.45	88.26	81.21
ET	87.32	79.99	87.13	79.08
RC	90.97	76.52	83.83	86.04
DRP-ARIMA	93.39	85.51	78.22	86.34
C3P-SMART	90.06	80.50	78.19	89.03
IF	90.09	83.09	77.59	75.57
LOF	89.48	84.41	75.78	77.85
HCIMUBA-AIMS	95.71	89.48	89.40	89.42

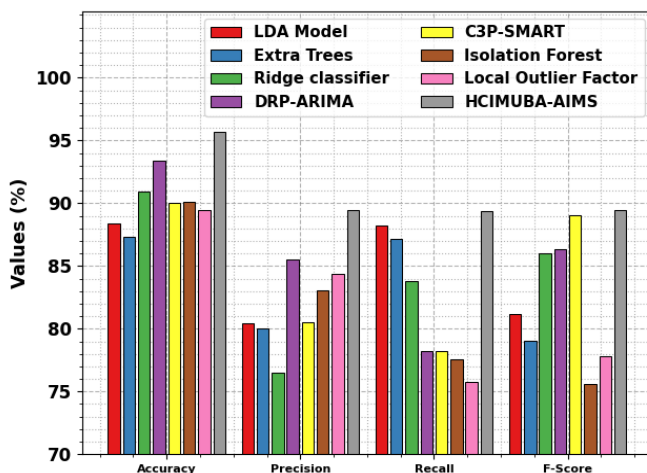


Fig. 6. Comparison study of HCIMUBA-AIMS approach with existing methods.

V. CONCLUSION

In this study, the proposed model of the HCIMUBA-AIMS approach aims to develop an accurate and effective model for analyzing user behavior in mobile applications using state-of-the-art models. Primarily, the data normalizer phase utilizes the LSN method for pre-processing. For the FS procedure, the IGWO approach is employed. Moreover, the proposed HCIMUBA-AIMS technique executes a hybrid CNN-BiLSTM-STA technique for classification. Ultimately, the HHOA fine-tunes the hyperparameter values of the CNN-BiLSTM-STA technique perfectly and results in better detection. The efficiency of the HCIMUBA-AIMS method is validated under a benchmark dataset. The validation of the HCIMUBA-AIMS method illustrated improved performance over existing techniques.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the Kaggle repository at <https://www.kaggle.com/datasets/valakhhorasani/mobile-device-usage-and-user-behavior-dataset>, reference number [16].

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