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RESEARCH ARTICLE

Implementing a Transfer Learning for User Behavior Analysis and Prediction Using Preference-Dependent Model

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ABSTRACT The modelling and forecasting of personal conduct depend on the records that individuals contribute at some stage in the shared network. It is essential to conduct this analysis to forecast the pursuits, feelings, and personal options, ultimately resulting in a development in service efficiency. However, to get accurate predictions, it's far essential to triumph over the mission of information segregation and retaining precision in evaluation. This paper offers the preference-based predictive behaviour analysis (PPBA) approach to address this problem. This approach aims to achieve the best possible accuracy stage in the desired identity. A study primarily based on analysis is done on mutated and segregated data in the proposed methodology, which uses transfer learning. A more sophisticated understanding of consumer options is made possible through the system of segregation, which is completed by studying desire deviations from the attitude of many inputs. Diverse mutations in deviation sites are recognized during the learning method, which aligns options for various statistics. State validations are completed primarily based on an individual's preceding options and any novel deviations observed inside the present state of affairs. This involves figuring out novel deviations from preceding behaviours, which can be rooted in various person options, which, in the long run, results in the refinement of user conduct prediction and modelling across quite a few applications primarily based on social networks. The proposed PPBA achieves 14.82% high detection accuracy for different input values, 9.41% less analysis time, 7.49% less false positives, 9.5% less complexity, and 10.34% high preference ratio.

INDEX TERMS Behavior analysis, information processing, data analysis, transfer learning, user preferences.

I. INTRODUCTION

User Behavior Analytics (UBA) is a process that is ordinarily used in cybersecurity systems to facilitate stumbling on or

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apprehending folks and threats. UBA compared the recorded threats with formerly saved threats to discover the real cause of attacks [1]. UBA is based totally on certain patterns that can be fashioned with definite functions and conditions, which assist in perceiving uncommon conduct and threats [2]. UBA improves overall precision in the identification and recognition process, increasing users' protection and privacy against attackers. UBA is one of the emerging techniques mostly used in social media and web-based applications to find problems and threats by performing an analysis process [3]. Gathering the actual data set for analysis, UBA examines the user connectivity process, interaction among users, devices, etc. Data is saved in the database for future analytics, which provides the right data set for the UBA process [4]. The big data analysis framework is mostly used in UBA to determine user behaviour by performing analysis and detection. Analytics tools are used in the big data framework to understand the exact meaning of messages and conversations in the communication process. Tools help detect accurate user behaviours by comparing them with previously recorded data [5], [6].

Conducting the user behaviour evaluation procedure as part of user interaction analysis for enhancing user experience in E-commerce personalized recommendations, and threat detection in cybersecuirty environment is essential. The categorization system is vital because it uses the consumer's behaviour styles to set the statistics. Social records are typically used inside the class procedure to discover the behaviour styles by comparing them with certain features and patterns [7]. Users' movements are categorized using the Firebug swarm optimization (FSO) approach, which employs the long short-term memory (LSTM) approach [8]. Attaction mechanism is utilized in FSO approach. The FSO approach improves the American system's performance and reliability by increasing the accuracy charge of detecting the correct behaviour type. Gathering already evaluated and categorized data is the first step in FSO [9]. The categorization technique also uses machine learning (ML) strategies, enhancing the recognition method's accuracy ratio. ML method trains the statistics set with a previously gathered or recorded set of statistics to calculate the accurate sort of conduct type system [10]. ML algorithms such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Convolutional neural network (CNN) and Autoencoders are utilized in the context of UBA. User behaviour categorization uses the convolutional neural network (CNN) technique, which extracts functions to reveal patterns. Features that include verbal exchange content, which means motivation, context, and time, form the premise of the characteristic extraction technique. [11].

The UBA process plays an important role in social media and web applications in discovering the motive and aim of attackers, which helps protect users from unknown attackers. Most of UBA's detection and recognition capabilities are derived from machine learning (ML) algorithms and techniques [12]. Thanks to ML approaches, users have more faith in applications, which boosts cybersecurity systems' overall performance and efficiency. User activity can be accurately observed and recognized using the ML method [13]. In user behaviour analysis (UBA), a support vector machine (SVM) method determines user actions' detailed patterns and consequences. SVMs identify false alarms for users and organizations when identifying unusual behaviour, which helps to alert users and aids in diminishing the crime rate via social media. SVM is mostly used to increase the security and privacy of users by understanding the exact needs and causes of behaviour recorded by the database [14], [15]. To create a model that reflects usual interactions and activities, SVMs may be trained on patterns of normal user activity. The SVM may set a behavioural baseline by learning the typical user activities. The SVM can identify outliers once the baseline has been established. For instance, the SVM highlights unusual behaviours as possible security risks if a user's behaviour suddenly changes statistically significantly and unanticipatedly, such as when they access files they normally do not or log in from IP addresses that are new to them.

The novelty of the proposed PPBA model for user behaviour analysis integrates the pre-trained transfer learning models, user preference data, and enhanced feature representation.

The main contribution and novelty of the paper is

- Designing the preference-based predictive behaviour analysis (PPBA) approach to predict user behaviour in social networks accurately.
- Introducing the transfer learning for mutated and segregated data analysis in multi-source information inputs.
- The experimental outcome has been implemented, and the suggested PPBA model increases the detection accuracy, less analysis time, false positives, complexity, and a high preference ratio compared to other existing models.

The rest of the paper is followed by the Section II discussing the related works. Section III gives the details about the proosed Preference-dependent Predictive Behavior Analysis Method. Section IV provides a comprehensive discussion and results of the study. Section V conclused the outcome of the paper and give directions for future work.

II. RELATED WORKS

Song et al. [16] proposed a model of offline computing to help predict user behaviour. This study uses a competitive deep Q network to improve the prediction performance ratio, which is important in many ways. In addition to improving the service provided to users, the proposed method is used to reduce the weight. The proposed model improves the system's performance according to the test results, which show an improvement in the correct detection rate.

A method to improve the speed of intelligent radio transmission has been proposed by Iftikhar et al. [17] and is based on Bayesian game theory. The multi-equilibrium presents important data for the study that the proposed method produces. The evaluation process identifies both Nash and

TABLE 1. Analysis of existing works in the literature.

Author	Proposed Method	Main Findings	Research Gaps
Nguyen et al. [26]	Hybrid Generative Model	Increased accuracy in user behaviour prediction, improving overall system performance.	Lacks in detailed comparative analysis with other models.
Berdun et al. [27]	Collaborative Feature-Based Model	Improved efficiency and performance in user behaviour analysis, reducing prediction errors.	Lack of specific identification of collaboration features and patterns.
Ao et al. [28]	Location-Based Big Data (LBD)	Enhanced system performance through the utilization of LBD, improving accuracy.	Limited exploration of challenges related to LBD,
Sheng et al. [29]	Hierarchical Time-Based Directional Attention Network	Improved efficiency and performance in sequential USB, utilizing RNN for accurate behaviour detection.	There is insufficient discussion on the proposed hierarchical time-based model.
Wu et al. [30]	Stable Features Identification Method (SFIM)	Improved accuracy and prediction rates in USB using SFIM.	Limited exploration of stability features identification method.
Amirreza Fateh et al. [31]	Attention-Driven Transfer Learning	This study has reached a high precision, robust, cost-effective approach that handles multilingual handwritten numeral recognition across various languages.	High computational complexity
Bani Ahmad et al. [32]	User Data Analysis (UDA)	E-commerce enterprises using user data analysis to transform operations and consumer experiences are featured in case studies, providing lessons and best practices.	However, in contemporary e-commerce platforms, Multivariate Testing is required.
Samuel Oladiipo Olabanji et al. [33]	AI-Driven Cloud Security on Threat Detection	Improve threat detection accuracy.	Historical data for training and biased or incomplete data can lead to inaccurate results and potential discrimination.

Bayesian Nash equilibria. The proposed strategy outperforms conventional methods by improving system performance and making it feasible.

Li et al. [18] proposed a new approach by integrating temporal or topological dimensions of information for the user behaviour analysis process. Behavior patterns are distinguished based on long and short-term patterns or user interactions. The proposed strategy outperforms competing methods by improving system performance through accurate and precise forecasting.

A dynamic user behaviour analysis model based on competitive interactions was proposed by He et al. [19]. Online user behaviour analysis is a common application of the proposed method, as it provides a complete picture of how consumers feel about a company's offerings. Using temporal information stored in the database, the proposed robust model outperforms competing methods in terms of diagnostic accuracy.

Research on user behaviour in Office application (OA) was proposed by Yang et al. [20] using a heterogeneous information system model. The proposed method is widely used in OA systems that require connections and user memory to provide better services for future events. Multi-node matrices enter both user relations and topics for the analysis process. The experimental results show that the proposed method improves the system's performance and reliability.

In their recent work, Alharbi et al. [21] used deep neural networks to develop a new model for analyzing user behaviour. In this case, this study uses a CNN algorithm to decipher the intent and content of user messages. An important part of the study is how CNN evaluates behaviour using specific methods and features. According to the experimental findings, the proposed method improves the overall system performance.

Tian et al. [22] proposed a user behaviour prediction process for Social networks using heterogeneous information. User heterogeneous information embedding (UHIE) is used for prediction, which calculates patterns based totally on certain functions. Likewise, a graph neural community is used here to get customer data. The counselled UHIE method improves the gadget's efficiency and dependability compared to previous processes.

Zhang et al. [23] added a new consumer conduct evaluation technique using mobile social surroundings (MSE). Customers' closest lengthy-time period data are calculated using the optimization approach. The proposed MSE version is completed based on optimization and interaction processes, including the exact information about behaviour or patterns. The results of the experiments demonstrate that the suggested strategy improves the accuracy rate of predicting user behaviour.

Zhao et al. [24] proposed a new dynamic heterogeneous neural network (DHBN) for user behaviour prediction. The proposed method involves a graph neural network to find patterns from users' interactive and temporal behaviour. The proposed DHBN model improves the detection rate compared to other methods, which increases the overall system performance and feasibility.

The authors of Wu et al. [25] proposed a new method for predicting user behaviour using online interest features. Here, the data transfer is started to find the correct meaning and profile of the users, which are calculated using certain facial patterns and characteristics. Based on the experimental results, the proposed strategy improves the performance and

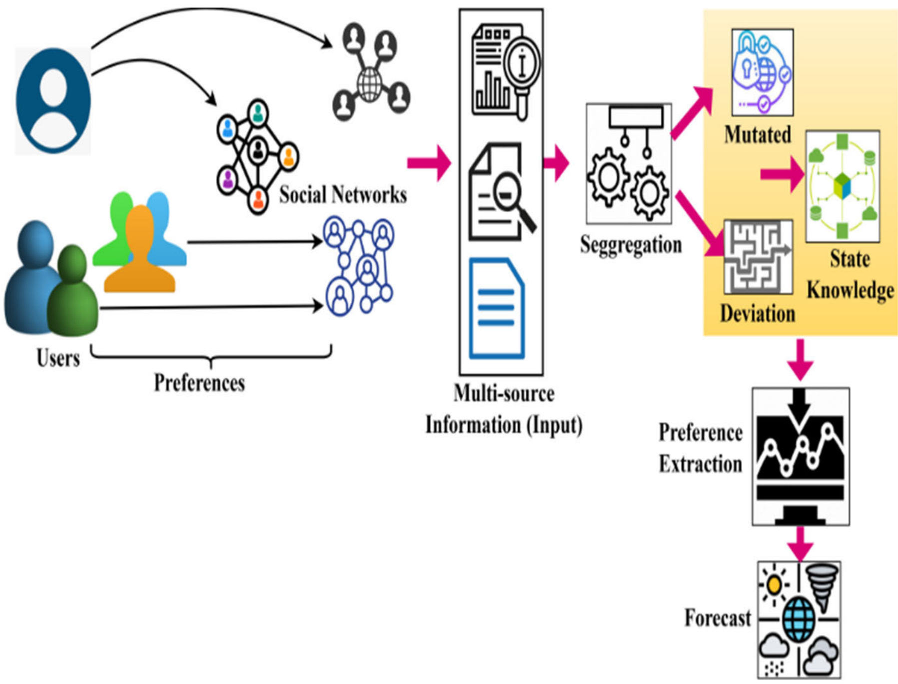

FIGURE 1. Proposed method.

reliability of the network by increasing the system's accuracy rate, navigation time, and delivery distance. The comparative analysis of existing studies in the literature is tabulated in Table 1.

III. PREFERENCE-DEPENDENT PREDICTIVE BEHAVIOR ANALYSIS METHOD

PPBA- aims to improve the reliability of user behaviour analyses based on different types of variable and non-variable data sources. Feedback is required from users (i.e.,) sharing information through social networks obtained at different times. This method of user behaviour aims to reduce negative emotions by analyzing the choice of providing convenience in the service operation. Data segmentation and optimization of the correct detection sequence based on the initial conditions of user behaviour is a major challenge. Examples of user behaviour are stored as data from previously known sequences. Figure 1 shows the proposed method.

User activities are seen and viewed through social networks. Data from multiple sources are categorized as modified or skewed. The user's actions are verified to the changed identity if they match the same data copied at the same time and day. On the contrary, phenomenological data highlights specific changes in the scattered areas according to the tendency of the mass information, the time of day when the successive event is observed, etc. Local knowledge and polling techniques reduce the likelihood of modelling user behaviour by reducing analysis time. An analysis period is a sequence of new disturbances or repeated data. The proposed user modelling approach addresses such a process by deviating the choice using transfer learning (Figure 1). Initial user behaviour modelling of sharing information through common networks let $S_i(T)$ represent the instance of sharing information detected or analyzed in a time interval such that the user's behaviour $U_b(T)$ is given as

$$\left.\begin{array}{c} U_b(T) = S_i(T) - N_d * S_i(T) \\ \textit{such that} \\ arg\min_{T} \sum N_d(T)\, \forall S_i(T) \end{array}\right\} \quad (1)$$

As in equation (1), N_d denotes the novel deviation and the objective of novel deviation minimization for all $S_i(T) \in U_b(T)$ is determined. The multi-source information inputs are segregated into two instances, namely mutated (M_u) and deviation (D_v). The $T = M_u + D_v$ such that D_v is observed in two M_u or vice-versa. If Z_T represent the number of sequences, then $D_v = (N \times T) - M_u$ is the preference deviation instances from multi-input that are to be divided. Let $P_r(M_u)$ and $P_r(D_v)$ denote the preference of $S_i(T)$ detected in Z_T interval and N_d is detected in all D_v such that

$$\left.\begin{array}{c} P_r(M_u) = Z_T * M_u + S_i(T), \forall N_d = 0 \\ \textit{and} \\ P_r(D_v) = \frac{N_d}{Z_T} D_v + N_d * S_i(T), \forall N_d \neq 0 \end{array}\right\} \quad (2)$$

As per equation (2), the multi-information preference observed and analyzed in the $(Z_T \times M_u)$ and $\left(\frac{N_d}{Z_T} \times D_v\right)$ sequences are segregated with $S_i(T)$. Now, based on the sharing information detection preference as in the above-derived equation (1), equation (2) is rewritten as

$U_b(T)$

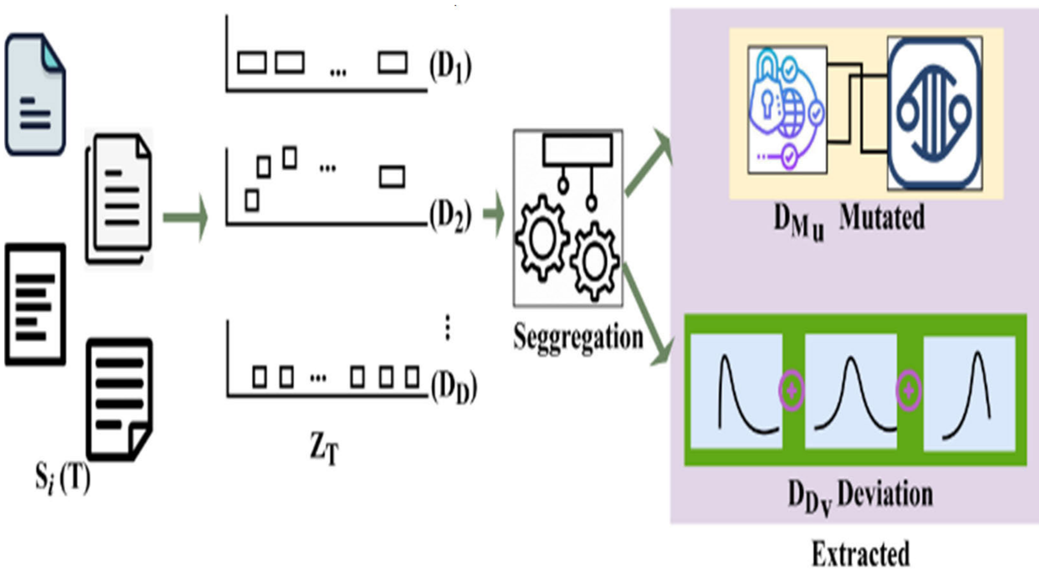

FIGURE 2. Data segregation process.

$$= \begin{cases} P_r\left(M_u\right) = Z_T * M_u + S_i\left(T\right), \ if \ \forall N_d = 0 \\ P_r\left(M_u\right) - P_r\left(D_v\right) = Z_T * M_u + S_i\left(T\right) - \dfrac{N_d}{Z_T} D_v \\ +N_d * S_i\left(T\right), \ if \ \forall N_d \neq 0 \end{cases} \tag{3}$$

In the above-expanded $U_b\left(T\right)$, the consequence of $D_v \in T$ is to be pre-estimated on noticing the first deviation instances D_v as in equation (4). This is assessed to detect N_d it was based on detection precision analysis using the transfer learning process. The data segregation and preference detection using the appropriate multi-source information is shared through the transfer learning process. From this information-sharing process, the consecutive sequence of $Z_T \in D_v$ is given as

$$Z_T\left(D_v\right) = \left(1 - \frac{M_u}{Z_T}\right) D_{v-1} + \frac{M_u}{Z_T} \sum_{i=1}^{T} \frac{\left(1 - \frac{M_u}{Z_T}\right)^{i-1} D_{v-i}}{T} \tag{4}$$

The above eq uation (4) follows the consequence of the previous preference D_{v-1} (i.e.) the previous preference instances are the M_u and therefore, $Z_T\left(D_v\right) = \left(1 - \frac{M_u}{Z_T}\right) D_{v-1} + \frac{M_u}{Z_T} \sum_{i=1}^{T} \frac{\left(1 - \frac{M_u}{Z_T}\right)^{i-1} D_{v-i}}{T}$. Hence, based on the above consequence, $U_b\left(T\right) = P_r\left(M_u\right) - P_r\left(D_v\right)\left[1 - Z_T\left(D_v\right)\right]$ is the final output for $N_d \neq 0$ conditions.

A. DATA SEGREGATION PROCESS

The data segregation method is exemplified in Figure 2. The input $S_i(T)$ is observed for D_D sequences for segregation (Refer to Figure 2). This observed data is classified based on $p_r\left(M_u\right)$ and $P_r\left(D_v\right)$ for mutated and deviation such that Z_T is precise. This is required to identify the behaviour change in user data analysis. Segregation is subject to use preferences and $U_b(T)$ as in equation (3). Equation (5) defines the data segregation metrics (D_{M_u}) and (D_{D_v}) for mutated and deviation cases at the first stage as

$$\left.\begin{aligned} D_{M_u} &\simeq \frac{P_r(M_u).C}{\sum_{i\in T}[Z_T * M_u * S_i(T)]_i} \\ D_{D_v} &\simeq \frac{P_r(M_u).C + P_r(D_v).C}{\sum_{i\in T}(Z_T * M_u)_i\{[1 - Z_T(D_v)] \times P_r(M_u)\}_i} \end{aligned}\right\} \tag{5}$$

Equation (5) calculates the data segregation of recognizing precision values found in M_u and D_v for the successive set C that was saved from the prior precision observation. During the first step of user behaviour modelling, the multi-source inputs for transfer learning are the initial and final estimates of D_{M_u}, D_{D_v}, $P_r\left(M_u\right)$ and $P_r\left(D_v\right)$. To identify the new discrepancy in data segregation among M_u and $D_v \in T$, the sequential precision processing is useful. In the following session, we will talk about this transfer learning process.

B. TRANSFER LEARNING PROCESS FOR USER BEHAVIOR MODELING

In the data segregation method, transfer learning analysis is aided in observing the correctness of D_{M_u} or D_{D_v} and evaluate N_d. From this transfer, learning relies on previously saved state knowledge of the $S_i(T)$, the more feasible detection precision is attainable. The total number of sequences may differ, although the saved state knowledge information assists to classify $S_i(T)$ for both the intervals and $Z_T(D_v)$ in all T. Instead, this learning process performs state validations based on previous preferences and novel deviations. In the consecutive difference estimation, D_v and M_u are observed to improve the saved state knowledge of $S_i(T)$. In particular, in the data segregation process, various sequences of precision detected $S_i(T)$ is augmented to increase the $U_b\left(T\right)$ along with the better solution and observation of novel deviation. From the

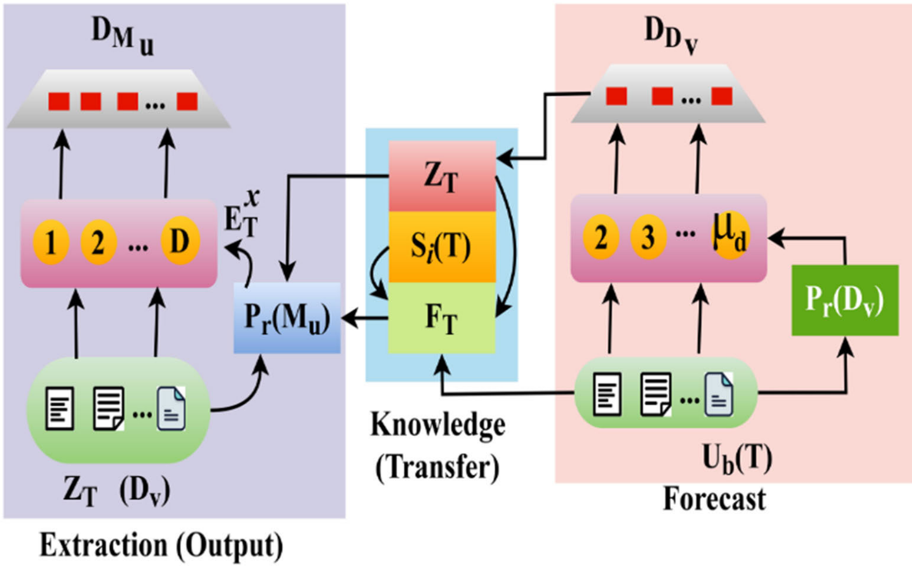

FIGURE 3. Output extraction and forecast learning models.

sequential processing, the multi-source information inputs for consecutive differentiation is $S_i(T)$ and T. The computation of $S_i(T) \in T$ is segregated under M_u and D_v relies on the existence of consequences. In feature extraction phase, user behavior data using text preprocessing cleans the text by removing stop words, punctuation, and special characters. Tokenization stage is split the text into individual words or tokens. Converting text into numerical representations using techniques like TF-IDF (Term Frequency-Inverse Document Frequency), Bag-of-Words (BoW), or word embeddings (e.g., Word2Vec, GloVe).

Data segregation makes use of preference extraction processing to distinguish between $S_i(T)$ and the time sequence. After estimating $Z_T(D_v)$ and $(Z_T T)$ for preference extraction processing, the transfer model is used to predict the starting state knowledge. The preference extraction output sequence $\left(E_1^x to E_T^x\right)$ is estimated using equation (6) as

$$\underbrace{\begin{array}{c} E_1^x = M_{u_1} \\ E_2^x = 2M_{u_2} - 2\,(D_v)_2 - P_r\,(M_u)_1 \\ E_3^x = 3M_{u_3} - 3\,(D_v)_3 - P_r\,(M_u)_3 \\ \vdots \\ E_T^x = Z_T.M_{u_T} - Z_T\,(D_v)_T - P_r\,(M_u)_{T-1} \end{array}}_{Preference\ Extraction\ Output}\Bigg| \\ \times \underbrace{\begin{array}{c} F_1 = M_{u_1} \\ F_2 = 2\,(D_v) + P_r\,(M_u)_1 \\ F_3 = 3\,(D_v) + P\,(M_u)_2 - P_r\,(D_v)_1 \\ \vdots \\ F_T = Z_T.\,(D_v) + P_r\,(M_u)_{T-1} *P_r\,(D_v)_{T-2} \end{array}}_{State\ Knowledge\ Forecast\ Sequence} \quad (6)$$

The process of preference extraction produces two outputs, namely M_u and D_v from $E_1^x to E_T^x$ sequences and forecast sequence $(F_1 to F_T)$. Data segregation is now carried out via machine learning based on the many occurrences at different time intervals. The data segregation criterion is when $T \in E^x$ is not equal to $T \in F$. F is calculated using D_v if the first instance of M_u's sequence occurs; this implies that T, differentiated according to the M_u norms, takes place, followed by Z_T. The forecasting series of the deviation cases is $(D_v) + P_r\,(M_u)_{T-1} *P_r\,(D_v)_{T-2}$. In the extraction process, the initial set is (E_T^x, M_u) from which (F_T, D_v) the data is segregated using a local information extract. In this observation, the comparison of E_T^x and F_T is validated such that $M_u = \{M_u \cup P_r\,(M_u)\}$ and $D_v = \left\{E_T^x \cap P_r\,(D_v)\right\}$ is identified and segregated independently. The forecast of the state knowledge is satisfied its first set from which the consecutive instance is distinct from the previous behaviour.

Separating the detection accuracy of the offending instance with T according to $P_r(D_v)$ in the occurrence instance follows the extraction method. For all T sequences discriminated under D_v, the state information forecast is used as the current set modelling metric, and the multi-source data inputs are $P_r(D_v)$ and D_v. The first step in data separation extraction is considering user preferences during design. The *ith* and *jth* column and row vectors in this separation stand for D_v and $S_i(T)$, respectively. When D_v and $S_i\,(T)$ stand for T, meaning $D_{M_u} < D_{D_v}$, the detected instance is determined. Instead, if $D_{M_u} < D_{D_v}$ is true, then the user preferences are differentiated from the behaviour analysis, the new consequence of M_u is further processed and segregated under E_T^x, where $T \in M_u$.

C. TRANSFER LEARNING FOR OUTPUT EXTRACTION AND FORECASTING

Figure 3 presents the transfer learning model for output extraction and forecast. The learning model relies on D_{M_u} and D_{D_v} for $Z_T\,(D_v)$ and $U_b\,(T)$ validations such that

($Z_T, S_i(T)$, *and* F_T) are the knowledge (transfer) set (Refer to Figure 3). This is required to improve the $P_r(M_u)$ and $P_r(D_v)$ segregation for deviation and preference extraction. In the preference extraction, F_T is updated based on $S_i(T)$ and Z_T whereas for the forecast, Z_T and $U_b(T)$ is required. In the preference extractions mentioned before, the statement "$D_{M_u} > D_{D_v}$" has been assigned as one, and the statement "$D_{M_u} < D_{D_v}$" is marked as zero. As shown in equation (6), the process of differentiating any M_u in D_v starts with E_T^x and F_T if the multi-information preferred occurrence of zero is observed. At this stage, this study acquires the conditional sequences to validate them using the transfer learning procedure and to make predictions based on the state knowledge.

The suggested PPBA processes the learning of $S_i(T)$ calculation. At the start of this observation procedure, the discovered D_v is helped with data segregation using the representations of $M_u \times P_r(M_u)$ and $M_u \times P_r(D_v)$, respectively. Using the separated D_v behavioural analysis $[S_i(T)]$ is necessary for the assessment procedure, where T is the detection precision method for extraction. In the state knowledge multi-source information retrieval, the (U_t, t_d) is extracted for user behaviour analysis to check if there are any M_u takes place. If M_u takes place, then the D_{M_u} is computed as in the above equation (5). Instead, using D_{D_v}, the D_v a consecutive instance is forecasted. The preference extraction process and forecast are classified from the data segregation process as presented using transfer learning. (7), as shown at the bottom of the next page.

An equation depicting the frequency of D_v for different time sequences and the unique frequency of M_u in D_v detection accuracy is shown above. If the prior preferred solution is true for either D_v or $M_{u-1} \in$ separate instance, wherein the projected value for M_u is zero, then M_u in D_v fulfils the equation $E_1^x = 0$. Therefore, this process is not considered in the extraction process. For both observations, the novel deviation is augmented before the state knowledge is forecasted as

$$\left.\begin{aligned} F_1 &= \frac{1(D_{v_1})+M_{u-1}}{D_{v_1}} \\ F_2 &= \frac{2(D_{v_2})+M_{u-2}}{D_{v_2}} - P_r(D_{v-1}) \\ F_3 &= \frac{3(D_{v_3})+M_{u-3}}{D_{v_3}} - P_r(D_{v-2}) \\ &\vdots \\ F_T &= \frac{T.(D_{v_T})+M_{u-T}}{D_{v_T}} - P_r(D_{v-T}) \end{aligned}\right\} \tag{8}$$

The state knowledge forecast is estimated at the end of all the D_v otherwise, before the start of the next M_u. In the state knowledge behaviour forecast, along with F_T, D_{D_v} is forecasted the user behaviour. Hence, the entire state knowledge holds the complete set of (F_T, D_v) and (F_T, D_{D_v}) wherein the initial stage, F_T indicates the forecast for M_u and the last denotes the D_v. It addresses either of the F_T (i.e.) extracted under M_u or D_v is behaviour forecast. As per the state knowledge, the modelling of users with multiple social network inputs D_v, D_{M_u} and N_d is used for the next computation of $E_1^x toE_T^x$ consecutive instance. In these criteria, the novel deviation is calculated as follows:

$$N_d = \frac{Z_T.x - P_r(M_u) * (D_{M_u}) + xT}{(Z_T + x)T * P_r(M_u) + P_r(D_v)} \tag{9}$$

The variable x represents the determined frequency of M_u in D_v, as shown in equation (9). The likelihood of preference selection in either M_u or D_v is used to validate the subsequent sequential instance using this new deviation. Hence, under M_u, the following result is obtained if $P_r(M_u) = true$, if $N_d = 0$. The multi-social community M_u is discovered if and only if $D_{M_u} > D_{D_v}$. In the same way, the forecast of $N_d = 0$ indicates that this network does not exist. Until the scenario mentioned above doesn't play out, M_u's detection precision is valid. Thus, x's incidence in M_u and D_v gradually segregated until it became constant due to mutation or divergence. Common techniques handle the finding of N_d by switching sequences from M_u to D_v or vice versa. Contrarily, there is some possible occurrence of M_u in D_v that is misguided as N_d; in the above state knowledge and preference extraction forecast and consecutive learning process, the detection precision-based verification increases the chances of harmonizing multi-information preference detection $M_u \in T$ and $M_u \in D_v$ to decrease the novel deviation in different time intervals.

D. BEHAVIOR MODELING PROCESS

Figure 4 presents the behavior modeling process. The inputs $Z_T(D_v)$, $U_b(T)$ and $Z_T(D_v)$, $S_i(T)$ are required for identifying deviations. The deviation detected outputs are classified based on previous $U_b(T)$ identified from $E_1^x toE_T^x$. This is performed using the F_T between different $S_i(T)$. Based on the N_D (elimination), the new models are sequentially extracted (Figure 4). Followed by the above sequential process, the user behaviour modelling of a human through different social networks is computed through a series of evaluations as per the equations (4), (6), (8), and (9) for both M_u and D_v follows.

$$\left.\begin{aligned} Z_T.M_u &= D_{M_u}.P_r(M_u) + E_T^x * S_i(T) \\ M_u &= \frac{1}{Z_T}\left[D_{M_u}.P_r(M_u) + E_T^x * S_i(T)\right] \end{aligned}\right\} \tag{10}$$

The E_T^x aided in equation (9) is derived from the consecutive sequence of M_u as in above equation (6) whereas the E_T^x Equation (10) is derived from equation (7) and estimated for its occurrence. Here, the user behaviour model (i.e.) $U_b(T)$ with a novel deviation N_d in D_v in $\frac{1}{Z_T}\left[D_{M_u}.P_r(M_u) + E_T^x * S_i(T)\right]$ is the final detected precision sequence of $S_i(T)$. If N_d and F_T are not computed, then the entire class of $U_b(T)$ will be extracted under $N_d \in D_v$ resulting in detection accuracy. Figure 5 illustrates the data segregation and $E_T^x(\%)$ for different $S_i(T)$.

In Figure 5, the data segregation and $E_T^x(\%)$ for different $S_i(T)$ is analyzed. For different D_{M_u}, D_{D_v} and deviations, the above comparisons are performed. The proposed method achieves a high D_{M_u} compared to D_{D_v} due to $Z_T(D_v)$ assessment. In the different F_T processes, the updates, and transfer are modelled based on $N_d \forall U_b(T)$. Contrarily for E_T^x, this is

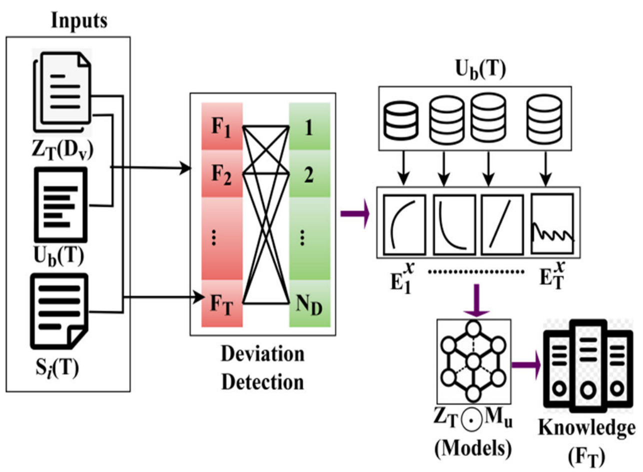

FIGURE 4. Behavior modeling process.

based on $Z_T\ (D_v)$ and $u_b\ (T)$ in the consecutive sequences. This contrary part is required for F_T in $P_r\ (M_u)$ and $P_r\ (D_v)$ processes such that the deviations are suppressed. Depending on the deviation detected, the segregation is performed. In the E_T^x process, distinct and cumulative instances are observed for $S_i(T)$. However, the N_d requires new segregation for different improvements in $P_r\ (D_v) \in Z_T\ (D_v)$. Figure 6 presents the analysis on $Z_T(D_v)$ and N_d for different F_T.

An analysis for $Z_T\ (D_v)$ and N_d due to varying F_T is presented in Figure 6. The $Z_T\ (D_v)$ is a prime factor for handling multiple $S_i(T)$ in preventing errors. This process is required for classifying further E_T^x through M_u and D_v differentiations. By segregating D_v from $S_i(T)$, the sequence remains undisturbed, maximizing accuracy. Besides, as the $Z_T\ (D_v)$ is identified with ease using $U_b(T)$ and $P_r\ (D_v)$, the N_d as per equation (9) through E_T^x is identified, improving the accuracy. Therefore, the N_D is comparatively less for different inputs; for lesser inputs, it is less. However, N_d is extracted from $S_i(T)$ and $U_d\ (T) \forall (Z_T.M_u)$ that is suppressed periodically. An analysis for detection accuracy for varying N_d is presented in Figure 7. For the varying N_d, the detection accuracy for different E_T^x is analyzed in Figure 7. The N_d detection mitigates the interference in E_T^x based on F_T; the F_T is modelled for extraction and forecast. On the contrary case, the D_{M_u} is exploited for $U_b(T)$ based on $Z_T.M_u$ such that detection accuracy does not fail. This process is non-recurrent, requiring multi-point T verification in $Z_T\ (D_v)$. Therefore, the different processes are performed for high detection accuracy, preventing further errors.

IV. RESULTS AND DISCUSSION

This sub-section discusses the performance discussion of the proposed method using MATLAB-based experimental analysis. The dataset [34] provides information on user preferences for web, university, mobile, gender, and custom terms through different social networks. Based on the user count (maximum of 916), the preference percentage using 14 different questionaries' is estimated. The preference leading to 0 is identified as a deviation point, and the sequential inputs up to 120 are accounted for in the analysis. The metrics detection accuracy, analysis time, false positives, computational complexity, and preference ratio are compared with the existing HGM [16], HTDA [21], and SFIM [29] methods.

A. DETECTION ACCURACY

Figure 8 represents the multi-source information processing for user behaviour modelling and sharing information based on segregated data under various predictions and detection precisions. In this proposed method, detected between mutated and deviation data observed from the (D_{M_u}) and (D_{D_v}). If either one condition fails, then $Z_T(D_v)$ or $Z_T(M_u)$ is achieved success in the transfer learning process, preventing $S_i(T)$ and therefore further state knowledge and preference extraction are not validated. The condition $U_b\ (T)$ achieves high success in user behaviour modelling, which is observed with mutated and segregated data, and hence, the multi-information preference is detected and has comparatively less analysis time. Similarly, if the novel deviation is identified for $\frac{N_d}{Z_T}$ estimation, and then preference deviations are required to process the further conditions. In this series of observations, the preference ratio is high in obtaining the sequential data segregation. Therefore, the state knowledge for multiple social network-based applications is high; detection precision requires multiple information, and therefore, the detection accuracy is high. As a result, there are fewer false positives, meaning behaviour forecasting cannot achieve its high detection accuracy goals.

B. ANALYSIS TIME

This proposed method analyses time and false-positive less novel deviation, as it does not provide user behaviour

$$\left.\begin{array}{c|c}\underbrace{\begin{array}{c}E_1^x = D_{v_1} \\ E_2^x = 2D_{v_2} + P_r\ (D_v)_1 + N_{d_1} \\ E_3^x = 3D_{v_3} + P_r\ (D_v)_2 + N_{d_2} \\ \vdots \\ E_T^x = T.D_{v_T} + P_r\ (D_v)_{T-1} + N_{d_{T-1}}\end{array}}_{for\ D_v\ based\ Sequence} & \underbrace{\begin{array}{c}E_1^x = 0 \\ E_2^x = P_r\ (M_u)_1 + 2M_{u_1} - N_{d_1} \\ E_3^x = P_r\ (M_u)_2 + 3M_{u_2} - N_{d_2} \\ \vdots \\ E_T^x = P_r\ (M_u)_{T-1} + T.N_{d_{T-1}}\end{array}}_{for\ M_u\ based\ Sequence}\end{array}\right\} \tag{7}$$

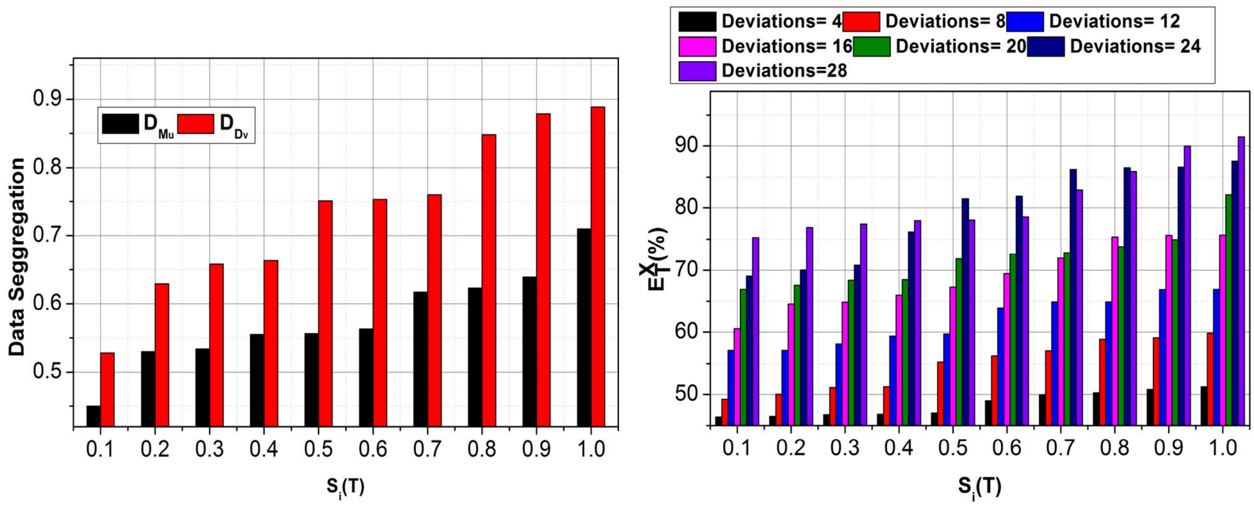

FIGURE 5. Data segregation and $E_T^x(\%)$ for Different $S_i(T)$.

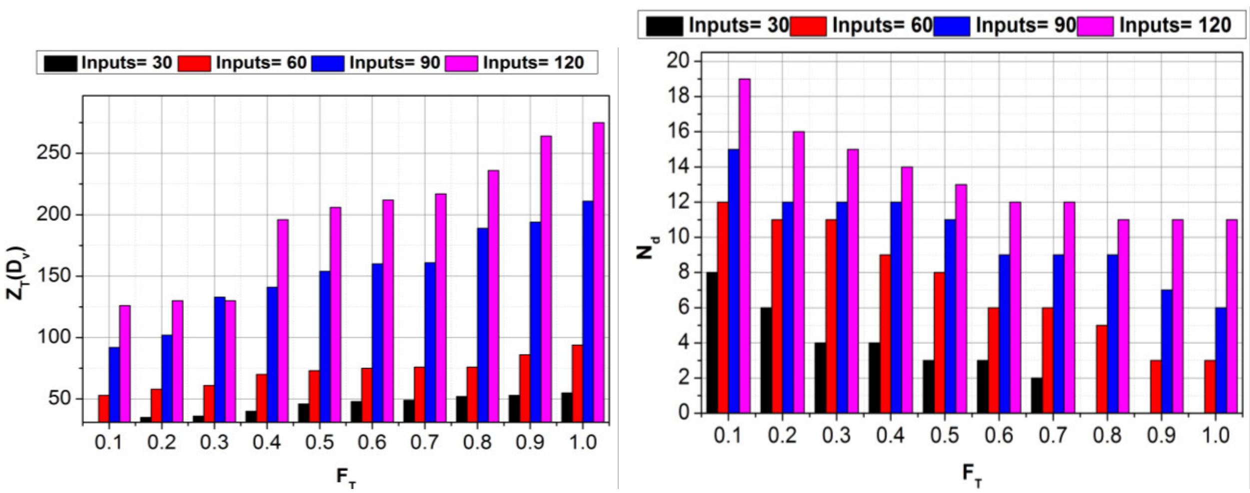

FIGURE 6. $Z_T(D_v)$ and N_d for different F_T.

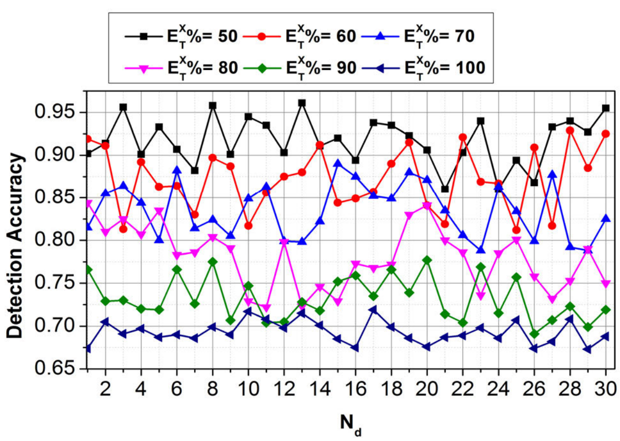

FIGURE 7. Detection accuracy for varying N_d.

analysis, detected between the different time intervals for multi-source information sharing through social networks. The segregated data required from the previous preference detection and analysis detection precision based on mutation and deviation data estimations for $(Z_T \times M_u)$ and $\left(\frac{N_d}{Z_T} \times D_v\right)$ in an interval. This issue is noticed by using the transfer learning process of the user behaviour analysis of $S_i(T) \in U_b(T)$ in previous observations, preventing novel deviation. The two conditions $P_r(M_u)$ and $P_r(D_v)$ are detected without augmenting the computational complexity. Similarly, the preference deviation of segregated data depends on state knowledge based on the preference extracted and forecasts due to replicated data providing a sequence of estimations for user behaviour modelling access in social networks. The user behaviour model observation processing multi-information preference will be evaluated in various detection precisions. The preference extraction is computed for providing data segregation, preventing behaviour forecast, and novel deviation. This distinct mutation is applied for both conditions for which the proposed method achieves less analysis time, as illustrated in Figure 9.

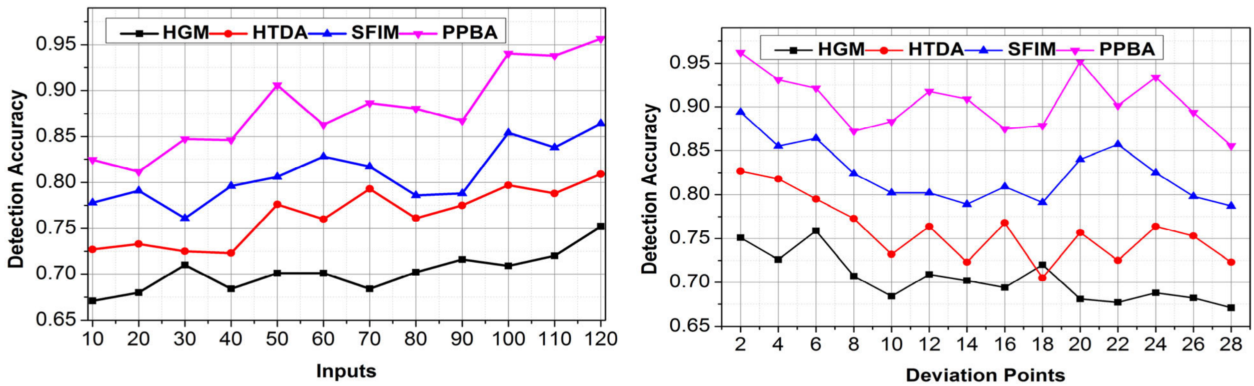

FIGURE 8. Detection accuracy.

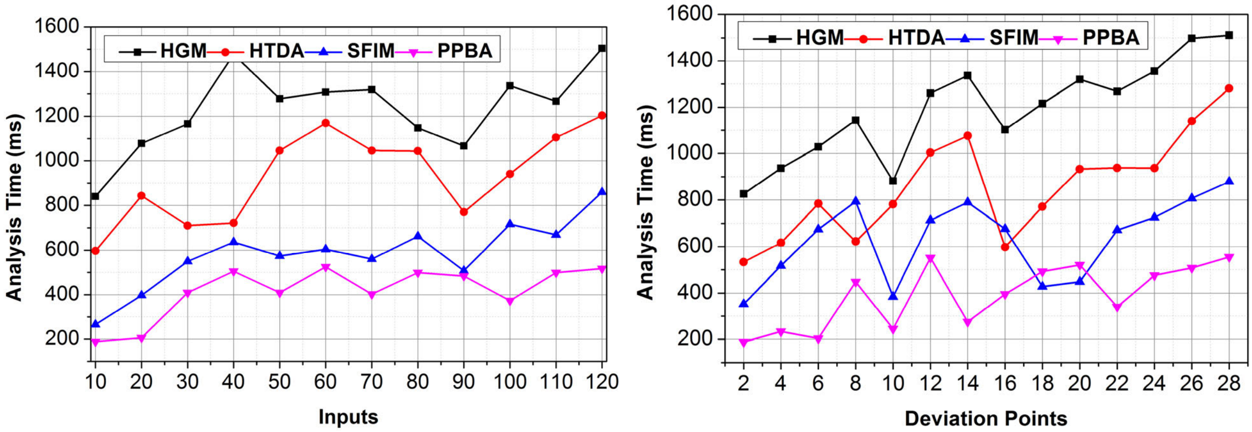

FIGURE 9. Analysis time.

C. FALSE POSITIVES

Figure 10 shows the investigation of unique deviation identification and detection precision for false positives. Through the estimation of the state of awareness and conduct forecast, this proposed method provides a reduction in false positives. In these detection-based observation intervals, $M_u = \{M_u \cup P_r(M_u)\}$ and $D_v = \left\{E_T^x \cap P_r(D_v)\right\}$ are detected based on varying user preferences. The multi-source information depends upon the $D_{M_u} < D_{D_v}$ preference deviations wherein the varying detection accuracy is preceded using the above-derived equations (6), (7), and (8) estimation. In this proposed method, the user behaviour modelling and information-sharing analysis condition of $(Z_T \times M_u)$ and $\left(\frac{N_d}{Z_T} \times D_v\right)$ is computed for analysis of timeless precision deviation and predictions. This series of estimations prevents different user preferences and behaviour modelling under different time intervals [as in equation (9)] and its preference extraction under independent mutations. As a result, there are fewer false positives than with the other variables used for user behaviour modelling. Based on this detection, the false positive is estimated for different user preferences and novel precision.

D. COMPUTATIONAL COMPLEXITY

This proposed method satisfies less computational complexity than the other metrics portrayed in Figure 11. The multiple social network-based information sharing and data segregation obtained for distributed detection precision in different time intervals are less for the proposed method. This is precise data segregation by detecting previous preferences and novel deviations from $M_u \times P_r(M_u)$ and $M_u \times P_r(D_v)$ for multi-source information. The transfer learning process is aided by observing the mutated data and multi-input sharing, which defines the computational complexity under different user preference instances. The condition $D_{M_u} < D_{D_v}$ precision detection and state knowledge-based computations are represented using behaviour forecast as in equations (9) and (10). Therefore, the behaviour modelling and multi-information preferences of social network information sharing based on intervals are returned for $P_r(D_v)$. Thus, the user behaviour modelling and information sharing sequence-based computational complexities and analysis time of the proposed method of behaviour forecast and detection precision-based state knowledge is less.

E. PREFERENCE RATIO

This proposed method achieves a high preference ratio for behaviour modelling and information sharing on social networks, and available data precision is utilized in the segregation process to provide behaviour forecasts (Refer to Figure 12). The preference ratio and information sharing are

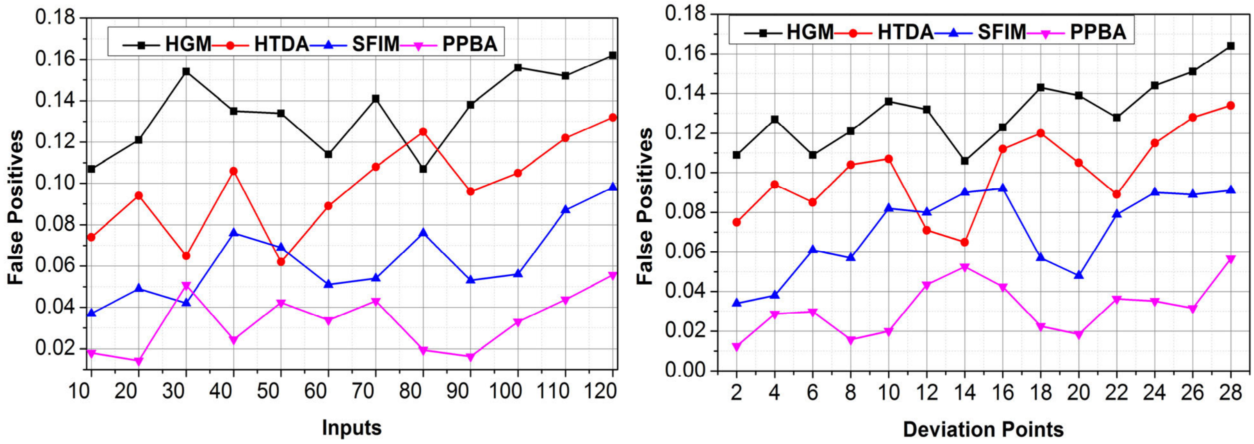

FIGURE 10. False positives analysis.

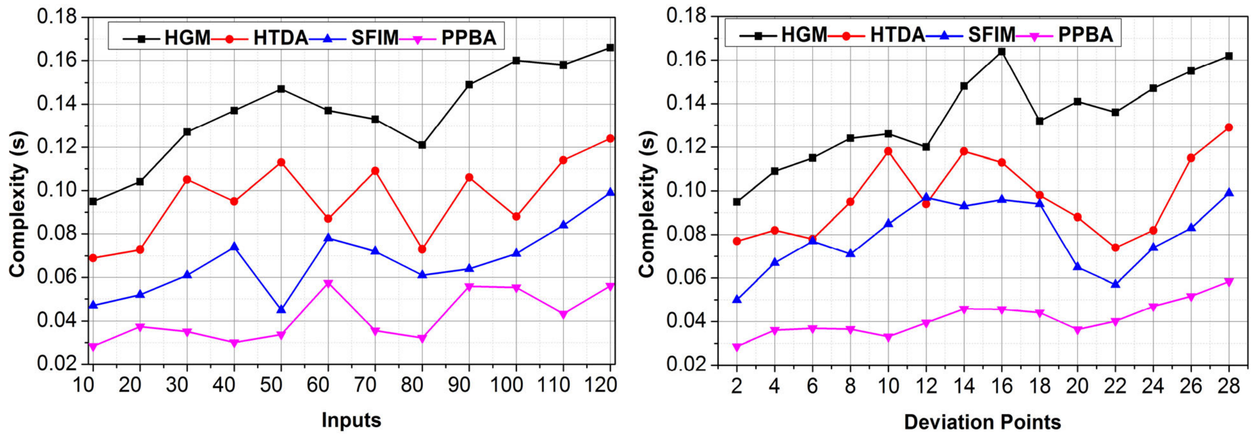

FIGURE 11. Computational complexity analysis.

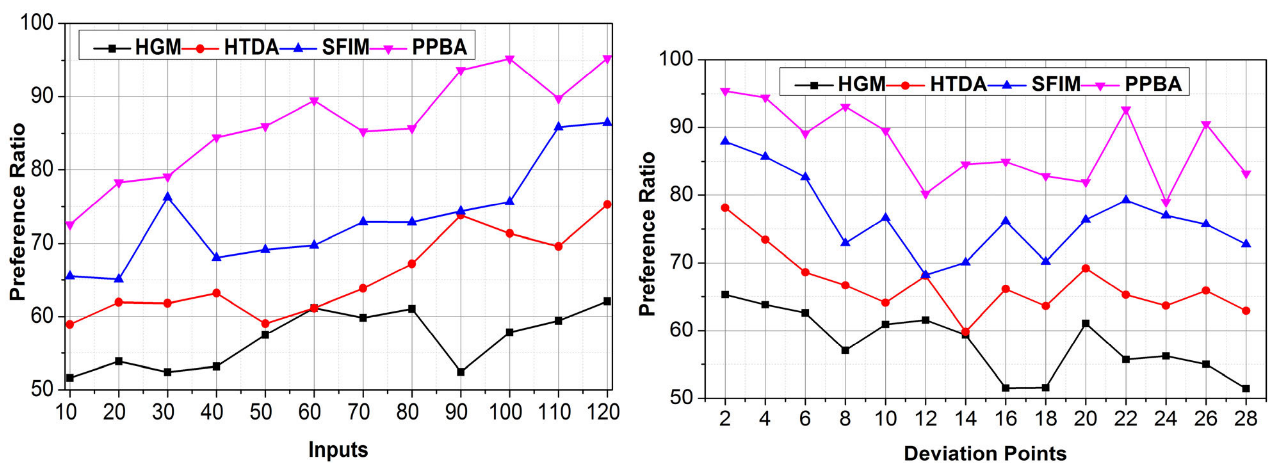

FIGURE 12. Preference ratio.

mitigated based on detection precision conditions for multiple social network-based applications and false positives due to distinct mutation and deviation data through transfer learning analysis. The state knowledge-based data sharing between different social networks is useful for detecting the user interests and analysis time of preference extraction with $(Z_T \times M_u)$ and $\left(\frac{N_d}{Z_T} \times D_v\right)$ based on different time intervals of precision detection using preference deviations computation and behaviour forecast observations. The mutated data is provided for both M_u and D_v instances. Hence, the novel deviation is computed to augment the preference ratio, which validates multi-source information and previous preference sequence, and therefore, the preference ratio is increased. The ratio is high in various user behaviours modelling social network information sharing and information processing for preference.

F. DISCUSSION

The proposed PPBA method is superior to other methods such as HGM, HTDA, and SFIM in terms of detection accuracy, decrease in analysis time, reduction in false positives, complexity, and preference ratio. In addition to achieving an amazing 95.65% detection accuracy, PPBA reduces analysis time by 9.41%, reduces the number of false positives by 7.49%, reduces complexity by 9.5%, and achieves a 10-34 per cent greater preference ratio. The analysis time has been reduced by 9.1%, the number of false positives has decreased by 7.3%, the complexity has decreased by 9.12%, and the preference ratio has increased by 10.41%. As a result of these findings, PPBA is an excellent way to boost detection accuracy, efficacy, and preference identification, making it a reliable approach for predictive behaviour analysis. The practical applications and implications of the transfer learning strategy for user behaviour analysis include E-commerce personalized recommendation, marketing, and cybersecurity fraud detection.

V. CONCLUSION

This article introduced a preference-dependent predictive behaviour analysis (PPBA) method for detecting user preferences from the input/ data accumulated from social networks. This method employs transfer learning to model two conditions: deviation and preference extraction. Based on the segregated data and knowledge transfer, the forecast is predicted for behaviour modelling. The proposed method handles multiple inputs across network analyses to improve preference accuracy detection. The learning states for deviation and information extraction are identified using forecast and previous behaviour models that reduce the analysis time. In this model, the input sequence and its interrupts due to novel deviations are segregated to prevent high complexity. The proposed PPBA achieves 14.82% high detection accuracy for different input values, 9.41% less analysis time, 7.49% less false positives, 9.5% less complexity, and 10.34% high preference ratio. However, the scalability of transfer learning methods in handling large-scale user behaviour data has not been thoroughly examined. Future studies will investigate the use of meta-learning to enable models to adapt to new user behavior patterns with large data quickly.

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