IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 24 May 2023, accepted 3 June 2023, date of publication 7 June 2023, date of current version 14 June 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3283932

RESEARCH ARTICLE

Human Micro-Expression: A Novel Social Behavioral Biometric for Person Identification

ZAMAN WAHID, ASM HOSSAIN BARI, FAHIM ANZUM, (Graduate Student Member, IEEE), AND MARINA L. GAVRILOVA, (Senior Member, IEEE)

Biometric Technologies Laboratory, Department of Computer Science, University of Calgary, Calgary, AB T2N 1N4, Canada

Corresponding author: Zaman Wahid (zaman.wahid@ucalgary.ca)

This work was supported in part by the Natural Sciences and Engineering Research Council (NSERC) of Canada by the Discovery Grant (DG) on Machine Intelligence for Biometric Security under Grant 10007544, in part by the Strategic Partnership Grant on Biometric Enabled Identity Management and Risk Assessment for Smart Cities under Grant 10022972, and in part by the Innovation for Defense Excellence and Security Network (IDEaS) Collaborative Project under Grant 10027075.

ABSTRACT The reliance on Online Social Networks (OSN) for both formal and informal social interactions has dramatically changed the way people communicate. In this paper, a novel Social Behavioral Biometric (SBB), human micro-expression, is introduced for person identification. An emotion detection model is developed to extract emotion probability scores from person's writing samples posted on Twitter. The corresponding emotion-progression features are extracted using an original technique that turns users' microblogs into emotion-progression signals. Finally, a novel social behavioral biometric system that leverages rank-level weighted majority voting to achieve an accurate person identification is implemented. The proposed system is validated on a proprietary benchmark dataset consisting of 250 Twitter users. The experimental results convincingly demonstrate that the proposed social behavioral biometric, human micro-expression, possesses a strong distinguishable ability and can be used for person identification. The study further reveals that the proposed social behavioral biometric outperforms all the original SBB traits.

INDEX TERMS Biometric security, emotion extraction, emotion progression signals, human micro-expression, natural language processing, person identification, social behavioral biometrics.

I. INTRODUCTION

Biometric systems are known for establishing an individual's identity based on distinctive physical or behavioral characteristics. Physiological biometric systems encode the physical traits of a person to build a template that is used for a person's recognition. Physiological biometrics such as fingerprint, iris, palm, face, and hand geometry, are most frequently employed [1], [2]. Unlike physiological biometrics, behavioral biometric systems emphasize behavioral patterns and actions a person innately possesses, including how a person speaks, walks, types, and signs documents [3], [4]. The advancement of social media has recently given rise to a new type of biometrics called Social Behavioral Biometrics (SBB). The domain of social behavioral biometrics studies a person's social interactions and communication patterns to establish the identity of the person [5]. As the number of users on social media platforms has exploded, Online Social Network (OSN) platforms have become a rich source of data that can reveal the critical traits of user's behavior. By using these behavioral footprints, SBB has been successfully applied in person authentication, anomaly detection, behavioral analysis, risk assessment, situation awareness, and other domains [5], [6].

Exploiting behavioral properties for biometric identification is an emerging research direction in the field of social behavioral biometrics. Recent researches have studied the retweet network, the Uniform Resource Locator (URL) network, the reply network, the hashtag network, and the temporal network as biometric traits [7], [8], [9]. Utilizing these social behavioral biometrics creates a pathway for the development of application for ensuring better cyberspace,

The associate editor coordinating the review of this manuscript and approving it for publication was Weizhi Meng.

security, and surveillance [10]. Furthermore, these SBB traits can be widely applied in digital banking [11], online fraud detection [12], [13], trustworthiness detection in social media [14], [15], sexual predators detection [16], understanding psychological states [17], mental illness prediction [18], and early depression detection [19].

Human micro-expression, also referred to as expressive emotion, is the behavioral reactions a person elicits to their day-to-day interactions in a social context. This paper, for the first time, considers human micro-expression extracted from text as an SBB trait and investigate an essential question whether expressed emotions have patterns when expressed in online social settings. Specifically, the following questions are answered:

- Does the progression of emotion (human micro-expression) over time exhibit a distinctive pattern among online social network users?
- Can human micro-expression be used as a social behavioral biometric for person identification?

The following contributions are made in this paper:

- A novel social behavioral biometric: human micro-expression, is introduced for the very first time in the field of Social Behavioral Biometrics.
- Emotion probability scores of each microblog posted by OSN users over a one-year period are extracted by the developed emotion detection system. These emotion probability scores are subsequently used to develop the proposed social behavioral biometric system.
- A novel algorithm is introduced to generate emotion signals and the corresponding emotion-signal maps of a user, generated while maintaining the temporal order of tweets. Furthermore, the emotion-progression features are extracted for training machine learning classifiers.
- A rank-level fusion technique based on weighted majority voting is applied to perform user identification. The proposed method achieves high recognition rate on a benchmark dataset.

A performance comparison analysis between the proposed human micro-expression SBB trait and the original SBB traits is provided, to demonstrate that the proposed human micro-expression biometric outperforms all the original SBB traits introduced in [7] and [9]. The proposed human micro-expression biometric has a potential to become one of the most potent social behavioral biometrics, with additional research introducing more in-depth technical breakthroughs in emotion-progression representation. The proposed human micro-expression trait may be further used for person identification in online biometric systems.

The rest of the paper is organized as follows: Section II presents the existing research in the domain of SBB, section III describes the proposed methodology, followed by analyzing the experimental results in section IV. Finally, a conclusion is made with discussion of potential areas for further research.

II. LITERATURE REVIEW

Social behavioral biometrics is a relatively new area of research introduced in 2014 [5]. Since then, there have been follow-up research and innovation in the field of SBB [14], [16], [20].

The study [16] presents a social behavioral biometrics-based sexual predator detection system for online conversations. For the sexual predator identification system, the authors extract SBB attributes, including turn-taking and reaction time, from textual interaction data. The article shows how SBB features may improve online safety and detect potentially harmful individuals. In [20], an intelligent add-on method utilizing the SBB features is proposed to improve the personalized services and security in Internet of Things (IoT) devices. The authors demonstrate that by incorporating continuous verification intelligence in smart devices with SBB characteristics, a user verification rate of over 90% is achievable. Recently, extracting personality aspects of OSN users as a form of SBB feature was investigated in [14] to detect the trustworthiness of users. The method detects online trustworthiness with a high recognition accuracy, showing the potential of using SBB traits to improve trust in online interactions.

Sultana et al. [21] proposed the formal framework of unimodal and multi-modal SBB systems based on the users' social interactions and patterns. The same authors in [7] introduced a handful of social behavioral biometrics and discussed the theory known as Dunbar's number [22], according to which a person can only establish stable social relationships with 100×250 acquaintances. Although online social networks permit users to have thousands of social connections, research indicates that this theoretical cognitive limit also applies to OSN users [23]. This lends to the idea that the smaller set of friends with whom a user maintains long-term interactions may exhibit user-specific behavioral features. Based on this fact, one of the earliest types of social behavioral biometrics appeared to be a reply network [7], a social behavioral biometric that generates the statistical patterns of how frequently OSN users respond to their virtually connected acquaintances. Similarly, another SBB trait, retweet network, is established based on the fact that a user retweets a small set of preferred acquaintances [7]. The network is developed in a similar manner, with edges denoting retweet relationships and log frequencies of edge weights being calculated. Reportedly, the performance of the reply network is superior to that of the retweet network for person identification.

A hashtag profile [7] is proposed as an SBB trait that extracts the hashtag-sharing behavior of an user. The hashtag profile captures the interests and preferences of an OSN user online. A Term Frequency - Inverse Document Frequency (TF-IDF) [24] method was applied to all the available hashtags in the corresponding dataset to generate the weighted hashtag profile of a particular user. A URL network [7] is also introduced that extracts users' preferred online social platforms and sharing patterns in OSN. Since several social media platforms—Facebook, Twitter, YouTube, Instagram, etc.—are popular among OSN users, TF-IDF weights are used to build the URL network. The user recognition performance of the hashtag network is found to be superior to the URL network. However, the performance of both networks is inferior to reply and retweet networks. Further, a new SBB trait called temporal profile [25] is proposed, which uses the statistical temporal information about an individual's OSN activity for online user recognition. The temporal profile generates data such as the average probability of tweeting per day, the average probability of tweeting per hour, the tweeting pattern in seven-day intervals, the time of tweeting in seven days, etc. Based on the experiment, the temporal profile demonstrated the lowest performance compared to the other SBB traits.

Recently, the psychological aspect of an individual exhibited in social media interactions has grown in popularity as a research topic for identifying the better social behavioral biometric. The study [26] investigated the OSN users' social interactions represented in the form of microblogs and analyzed the distinctive contextual nature of microblogs using state-of-the-art contextual embedding techniques to comprehend and identify users' personalities reflected in online social interactions. In addition, the emotional stability of OSN users, which can be derived from the users' shared social interactions, has garnered a great deal of attention. In [27], [28], and [29], rigorous approaches were carried out to analyze the role of gender, which may influence the way people share their innate feelings on social media platforms. These studies reported that males and females express emotions differently through writing on OSNs.

One of the key takeaways from the psychological and emotional aspects of OSNs is that from users' social interactions online, the psychological and emotional states may be identified. However, to the best of our knowledge, it was not yet studied whether a person can be identified from their emotional patterns over time demonstrated in his or her social media interactions. Furthermore, in respect to the established SBB traits mentioned earlier, one of the primary limitations is that most of the SBB traits are highly dependent on the generation of statistical and count-based features. The efficacy of the SBB traits becomes significantly limited if insufficient data from each user exists to generate the statistical features [6]. The progression of emotion, introduced in this paper, maintains different emotion probability scores of a particular microblog at a given time without relying on any statistical and count-based features. Importantly, the emotion progression can track the changes in emotions across multiple microblogs, allowing to dynamically evaluate the similarity across the sets of microblogs during a specific time period. Hence, the progression of emotion can be a suitable SBB feature to represent a person uniquely, overcoming the drawback of the prior SBB traits. Finally, the progression of emotion can offer a novel way to comprehend a person's emotional and psychological states, which is not achievable with the contemporary SBB features.

III. METHODOLOGY

A. OVERVIEW

This research introduces a novel social behavioral biometric, human micro-expression, for person identification online. An emotion detection model is initially trained and optimized to extract emotion probability scores from microblog samples of OSN users. The developed emotion detector extracts the emotion classes of angry, fear, sadness, love, joy, and surprise along with their corresponding probability scores from each microblog. Furthermore, multiple emotion-progression signals are generated for each of the users. Dynamic Time Warping algorithm [30] is then utilized to extract emotion-progression features which represent the similarities across emotion signals over time. Later, the extracted emotion progression features are used to train machine learning models to identify users. Lastly, rank-level fusion with weighted majority voting, also known as weighted Borda count [31], is utilized to the identification rate of the individual classifier to improve the accuracy of person identification. The overall architecture of the proposed system is depicted in Fig. 1.

B. EMOTION EXTRACTION

The emotion detection model developed in this work takes a single microblog as an input and calculates the probability scores of six emotion classes: anger, fear, sadness, love, joy, and surprise. These emotion classes are chosen due to the availability of a relevant and benchmark dataset with sufficient data that are crucial for developing an emotion detection model as accurately as possible in terms of its performance. The system performs standard text preprocessing techniques by removing hashtags, punctuations, URLs, stop-words, etc., followed by tokenization and Porter stemming [32]. For feature extraction, a frequency-based vectorization technique called TF-IDF [24] is utilized. TF-IDF is a widely used feature extraction technique that captures the importance of a word in a document corpus. It assigns a weight to each term based on its frequency of occurrence in the document, and inversely proportional to the number of documents in the corpus that contain the term [24] This allows for accurate sentiment and emotion analysis, information retrieval, and text classification. For emotion detection, in particular, TF-IDF is still widely used because it is faster than most of the deep learning-based pre-trained models and provides similar results [33], [34].

After the final input representation is created by the extracted features, Support Vector Machine (SVM) [35], Extreme Gradient Boosting (XGBoost) [36], and Multinomial Naïve Bayes (MNB) [37] models are trained. The hyper-parameters are tuned using grid search cross-validation [38] technique. According to the experimental results, XGBoost outperformed SVM and MNB for emotion extraction. Therefore, XGBoost is chosen to extract probability scores of the six emotion classes.

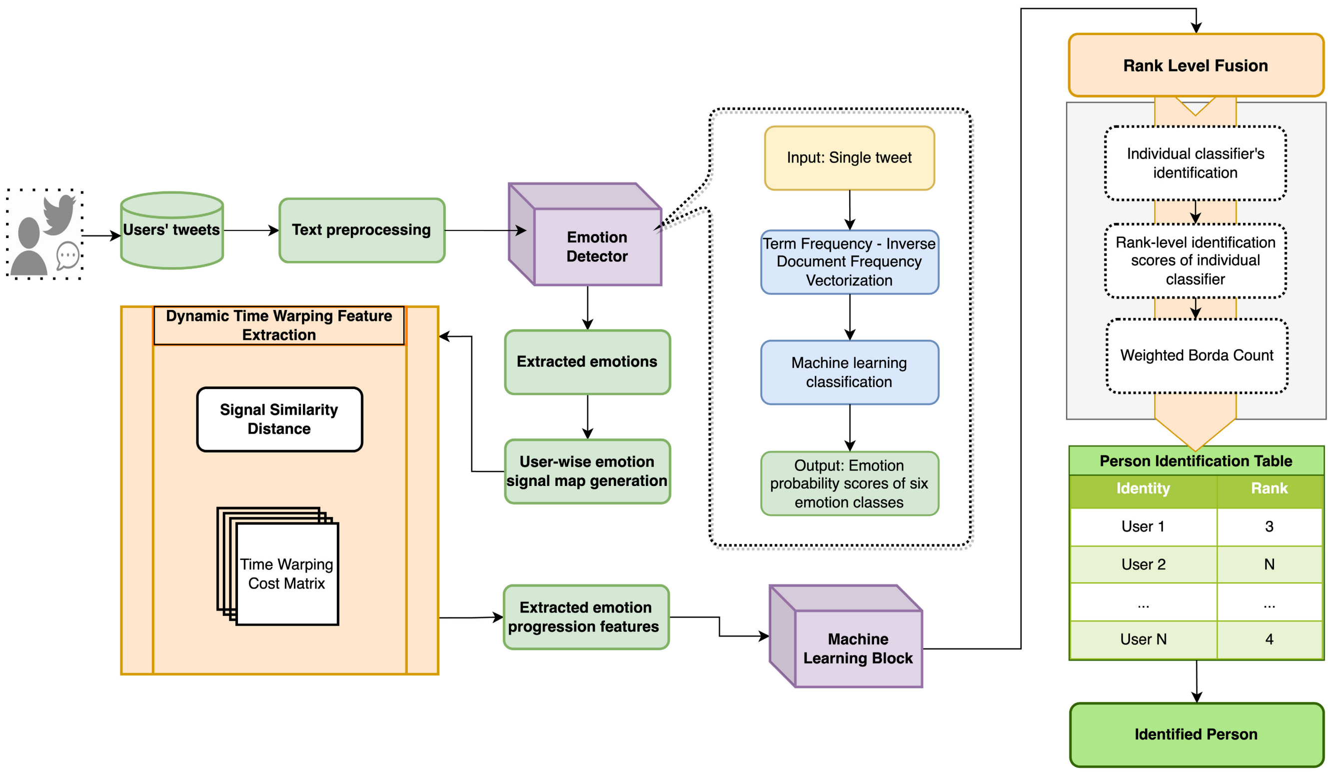


FIGURE 1. Overall architecture of the proposed method.

C. PROPOSED EMOTION SIGNAL REPRESENTATION

One of the primary contributions of this research is to represent users' expressed emotions extracted from their writing samples as emotion signals.

We propose the following strategy to effectively represent the progression of emotions of a person. Let N be the total number of available microblogs of a user and m be the number of microblogs to be considered to construct an emotion signal. Thus, an emotion signal, E_s, of a user can be represented using formula (1):

$$E_s = \left\{e_i, e_{i+1}, e_{i+2}, \ldots, e_m\right\}, i\epsilon[1:m], m\epsilon[1:N] \quad (1)$$

where e represents the emotion probability score of a single emotion class of i^{th} microblog of a user represented over time. The index of microblogs, i, in an emotion signal is defined as $i = \{1, 2, 3, \ldots, m\}$. The total number of unique emotion signals of a user that can be constructed from the available microblogs is denoted by t:

$$t = \frac{N}{m} \quad (2)$$

where t is the floor or ceiling integer value of the resulting number. This allows the proposed method to function even when the emotion signals are not equal in length. Therefore, the set of unique emotion signals of a user is:

$$E = \left\{E_s^1, E_s^2, E_s^3, \ldots, E_s^t\right\} \quad (3)$$

Each E_s in set E denotes a unique emotion signal from a specific time period that can be constructed using the formula (1). The order of E_s is followed linearly in order to make the emotion signals, E, successive to its precedent signal. The first emotion signal in E constructs from index, $i = 1$ through m and the following signals follow the successive order of the indexes. For instance, we have 200 microblogs (i.e. tweets) with the corresponding timestamps of a user, and our goal is to reflect the progression of the user's emotion signals. The order of the microblogs is sorted from the oldest to the latest. Now, let's consider $m = 50$ microblogs to construct a single emotion signal. Thus, E_s^1 represents the expressed emotions of the first 50 microblogs. E_s^2 represents the expressed emotions of the next 50 microblogs. The following 50 is for emotion signal E_s^3, and finally with the last 50 microblogs' expressed emotions, the emotion signal E_s^4 is constructed. So, a total of four unique emotion signals, $E = \{E_s^1, E_s^2, E_s^3, E_s^4\}$, can be generated. In summary, from the full set of N time-ordered tweets, a total of t unique emotion-signals can be constructed with m tweets each.

One of the primary objectives is to measure the emotion signal similarities and establish emotion-progression similarity patterns of an individual. To measure and extract similarity features from the available emotion signals of a user, only two emotion signals can be compared at a time. Hence, it is essential to find a way to generate the list of emotion-signal pairs in a unique manner that can be used for emotion-progression feature extraction. Therefore, to preserve the order of emotion signals and maintain the concept of emotion progression, a unique combination of emotion-signal maps is generated. Here, an emotion-signal map refers to a distinct pair of emotion signals that can be used for calculating the corresponding similarity features maintaining the progression of emotions over time. By applying the following combinatorial theory [39] without including the same emotion-signal pair twice, we can determine the total number of possible emotion-signal pairs and obtain the corresponding maps of a user:

$$^{l}C_{k} = \frac{l!}{k!(l-k)!} \tag{4}$$

where l denotes the total number of available emotion signals, and k symbolizes the number of emotion signals to be chosen from l to generate the emotion signals map. Since–in retrospect to the example given earlier–we have a total of 4 unique emotion signals for a user, and we can only compare the similarity among two emotion signal patterns at a time, the value of k is thus always 2. Therefore, the total number of combinations of possible emotion-signal maps is 6, based on equation (4). And the emotion-signal maps are:

$$\begin{array}{c} E_s^1 \longleftrightarrow E_s^2 \\ E_s^2 \longleftrightarrow E_s^3 \\ E_s^3 \longleftrightarrow E_s^4 \\ E_s^1 \longleftrightarrow E_s^3 \\ E_s^2 \longleftrightarrow E_s^4 \\ E_s^1 \longleftrightarrow E_s^4 \end{array}$$

where $\longleftrightarrow$ symbol identifies which emotion signal is mapped to which emotion signal in order to calculate the similarity features.

Since the emotion probability scores are in six classes, for every emotion label, six emotion-progression samples are constructed for every user. We extract the progression of emotion over time in different time intervals to capture unique emotion signals. In addition, the emotion-progression patterns can be constructed starting from and ending at any given point. Furthermore, we introduce an additional improvement to the proposed emotion signals representation method to capture the emotion-progression pattern of a person more efficiently and effectively. The idea is to update the first i^{th} index-value in equation (1) with an n_s number of skipped microblogs. This process is repeated using equation (3) to capture more emotion signals. The iterations continue until n_s reaches the last possible index in the available microblogs of a person, where no more emotion signals can be generated. Hence, the technique of using formula (1) proceeds as follows:

$$\begin{array}{c} REPEAT\ until\ n_s\ is\ valid: \\ E_s = \left\{ e_i, e_{i+1}, e_{i+2}, \ldots, e_m \right\} \end{array}$$

where the i is updated by n_s in every iteration. Essentially, after the initial phase of creating emotion signals with m microblogs each from N time-ordered microblogs of a user, the process continues, but starting from the n_s skipped indexes in N in its every successive iteration.

Assume the value of n_s is 20, meaning that in the second iteration of generating the emotion-progression signals, the signals will be constructed from 21^{st} to 70^{th} microblogs, 71^{st} to 120^{th} microblogs, 121^{st} to 170^{th} microblogs. In this specific example, during its subsequent iterations, the emotion signal construction starts from the index 41^{st}, 61^{st}, 81^{st}, and so on. The iteration stops when at least a pair of emotion signals cannot be generated anymore, since two emotion signals are required at a time to extract the features. With this proposed method, an increased number of emotion signals can be generated that capture better emotion-progression patterns of an individual. It should be mentioned that the concept of generating unique emotion signals in iterations is applied to each of the six emotion classes that represent the final set of emotion signals of a user.

The proposed emotion-signal map generation method is described in Algorithm 1. The algorithm takes the available microblogs of a user (M), the number of microblogs to be skipped (N_s), and the emotion signal length (N_t) as the input. In this case, the corresponding values of M, N_s, and N_t are 200, 20, and 50 respectively. Then it generates the emotion signals and their corresponding emotion-signal maps. Finally, the algorithm returns the emotion-signal maps as the output. The duplication filter check is performed across the iterations so that no duplicated signals are inadvertently considered to represent the final emotion signal maps of a user, which can lead to any unintentional biases. The algorithm repeats the process for every available emotion class.

Algorithm 1 Proposed Emotion-Signal Map Generation Algorithm

Input: Available microblogs (M), no. of microblogs to be skipped (N_s), signal length (N_t)
Output: Emotion-signal maps (S_{tm})

```
for every emotion class do
    Initialize,
    S = empty list of signals
    S_m = [ ]
    S_tm = [ ]
    N = length(M)
    r = 0
    while r < N − N_t do
        S ← GENERATE signals from M
        s ← FIND duplicate signals in S
        if s is not empty then
            REMOVE s from S
        end if
        S_m ← GENERATE signal map from S
        S_tm ← APPEND S_m to S_tm
        r ← N_s + r
    end while
    RETURN S_tm
end for
```

D. PROPOSED METHOD FOR EMOTION-PROGRESSION FEATURE EXTRACTION

Probability scores of six emotion classes for each of the tweets are used to represent emotion signals for every user. Emotion signals are used to extract emotion-progression features based on the similarities of between pairs of emotion signals. To find out the similarity between two emotion signals, we use Dynamic Time Warping (DTW) [30] which has widely been used to measure the similarity of human walking patterns, speech, data mining and time series clustering, and many more [40]. We use the DTW algorithm to compare and extract similarity features between emotion signals due to its flexibility and ability to recognize similar patterns with varying phases while reducing the impacts of time shifting and distortion by permitting stretchy adjustment of time-series data [40].

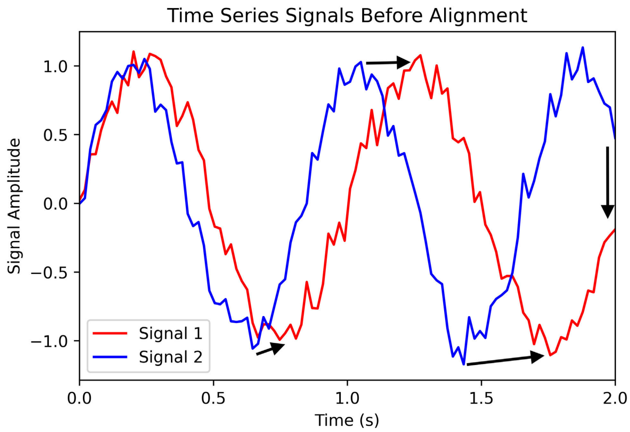


FIGURE 2. Raw time-series sequences showing the expected points to be aligned.

Fig. 2 demonstrates a two time-series signals and where the points are to be aligned. When two time series signals are given, $S = (s_1, s_2, \ldots s_N), N\epsilon\ \mathbb{N}$ and $S' = (s_1, s_2, \ldots s_M), M\epsilon\ \mathbb{N}$ represented by sequences of values, the DTW produces the best solution in $O(MN)$ time by measuring the similarity score of these two signals. As the first step, a cost matrix $C\epsilon\ \mathbb{R}^{N\times M}$ is built using the following formula [40]:

$$C\ \epsilon\ \mathbb{R}^{N\times M} = |S_i - S'_j|,\ i\epsilon\ [1:N],\ j\epsilon\ [1:M] \tag{5}$$

The DTW algorithm then finds the alignment warping path between S and S', that passes through the low-cost regions of C. The warping path refers to the alignment between the two time-series signals that minimizes the distance between them. Specifically, it is a sequence $p = (p_1, p_2, p_3, \ldots, p_L)$ with $p_l = (n_l, m_l)\epsilon[1:N]\times[1:M]$ for $l\epsilon[1:L]$ following three constraints described in [40]. The total cost c_p of a warping path p is defined [40] as:

$$c_p(S, S') = \sum_{l=1}^{L} c(S_{n_l}, S'_{m_l}) \tag{6}$$

where $c(S_{n_l}, S'_{m_l})$ is the local cost measure (more details can be found in [40]). A global DTW cost matrix is then built calculating the optimal warping paths with the following DTW distance function [40]:

$$DTW(S, S') = min\ \{c_p(S, S'), p\epsilon\ P^{N\times M}\} \tag{7}$$

where the set of all possible warping path is $P^{N\times M}$. The global DTW cost matrix, D_m, is calculated by the following equations [40]–

(1) First row:

$$D_m(1, j) = \sum_{k=1}^{j} c(S_1, S'_k), j\epsilon[1, M] \tag{8}$$

(2) First column:

$$D_m(i, 1) = \sum_{k=1}^{i} c(S_k, S'_1), i\epsilon[1, N] \tag{9}$$

(3) All other cells:

$$\begin{aligned} D_m(i,j) = min\{&D_m(i-1, j-1), D_m(i-1, j), \\ &D_m(i, j-1)\} + c(S_i, S'_j),\ i\epsilon[1, N], j\epsilon[1, M] \end{aligned} \tag{10}$$

The last element of the optimal warping path lies in D_m is the similarity score between two time-series sequences. The DTW cost matrix represents the warping paths among different data points between two sequences.

During the proposed emotion-progression feature-extraction process, DTW similarity distance score between two emotion signals and the corresponding DTW global cost matrix (time-warping cost matrix) are the key components. The first step for emotion-progression feature extraction is considering a single emotion class at a time. Then, from all the available unique emotion signals, the method selects every emotion-signal map that consists of two unique emotion signals. Then applying the DTW method described above, the proposed system extracts the corresponding DTW similarity distance between two emotion signals (a single emotion-signal map). That is, from a pair of emotion signals, the system produces a single similarity distance. The lower the distance, the more similar the emotion signals are. Alongside calculating the similarity distance between emotion signals, the method extracted the DTW cost matrix and used that feature for training the models. This feature is a representation of how one signal can be warped to another signal. Fig. 3 illustrates the process of emotion-progression feature generation where the input is two emotion signals and the output is the corresponding emotion-progression features.

In the proposed method, 50 microblogs is found to be optimal to construct a single emotion signal. If less than 50 microblogs are considered, the emotion signal is too short to generate discriminatory DTW features. On the contrary, with the number higher than 50, it reduces the number of emotion signals that can be generated because every user has only 200 microblogs. If the size of the DTW global cost matrix is represented by w_s and the lengths of two emotion signals are denoted by n and m respectively, therefore, w_s can be determined using equation (11)

$$w_s = n * m \tag{11}$$

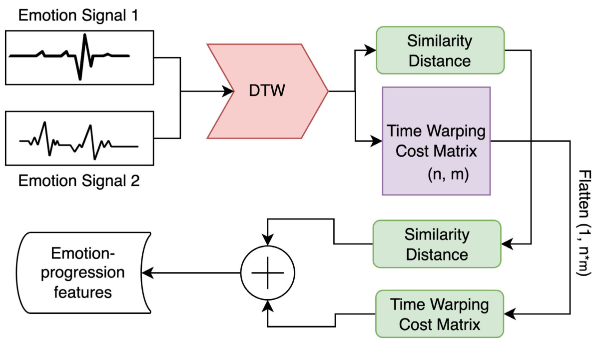


FIGURE 3. Proposed method for emotion-progression feature extraction.

If the total number of available emotion classes is e_n, then the final length of the emotion-progression feature set f_e, can be calculated using equation (12),

$$f_e = e_n(s_d + w_s - 1) \tag{12}$$

where s_d is the DTW similarity distance between two emotion-progression signals. Since the similarity distance s_d is essentially extracted from w_s, thus 1 is subtracted from w_s representing the ultimate length of f_e. The proposed algorithm for the emotion-progression feature extraction is presented below:

Algorithm 2 Proposed Emotion-Progression Feature Extraction Algorithm

Input: Emotion-signal maps (E_m)
Output: Emotion-progression features (D_d, C_m)

Initialize,
D_d = *empty list of DTW distances*
C_m = *empty list of DTW cost matrices*
for *every signal map* e, *in* E_m **do**
  $n \leftarrow length(e[0])$
  $m \leftarrow length(e[1])$
  $c \leftarrow$ *DTW cost matrix*, $D_m(e[0], e[1])$
  $d \leftarrow$ *DTW distance*, $c[n-1, m-1]$
  $D_d \leftarrow$ *APPEND* d *to* D_d
  $C_m \leftarrow$ *APPEND* c *to* C_m
end for
RETURN D_d, C_m

The input of algorithm 2 is the emotion-signal pairs that are the output of algorithm 1. From the emotion-signal maps, algorithm 2 extracts the DTW distance and time-warping cost matrix for every emotion-signal map. In algorithm 2, the DTW cost matrix function D_m uses the equation (8), (9), and (10) to calculate the corresponding DTW time-warping cost matrix of an emotion signal map. Then the DTW distance is calculated from the cost matrix. Finally, algorithm 2 returns all the calculated DTW distances and cost matrices, collectively referred to as a person's emotion-progression features.

E. CLASSIFICATION WITH RANK-LEVEL WEIGHTED MAJORITY VOTING

The final part of the proposed method is to feed the extracted emotion-progression features to an ensemble of machine learning models for person identification. This block learns the emotion-progression patterns of users and aids decision making during testing on unseen data. Initially, three classical machine learning algorithms: Random Forest [41], Extreme Gradient Boosting (XGBoost) [36], and CatBoost [42], are trained using the extracted emotion-progression features. Then a rank-level fusion technique is performed to enhance the person identification performance.

Random Forest is an ensemble of decision tree classifiers where each classifier predicts a class, and the class with the most votes among the decision trees is the model's final prediction [41]. A key feature of Random Forest is that the decision trees maintain an uncorrelated relationship, which contributes to the model's improved performance. As found experimentally, the method develops an optimal solution, balancing training time and performance costs, using 400 trees. In addition, an XGBoost algorithm is trained for person identification, employing a parallel tree gradient boosting technique. It produces superior outcomes with reduced computation time and memory usage. It takes advantage of sparse awareness, which can automatically handle missing values in data [36]. The proposed method develops 400 concurrent trees for extreme gradient boosting. Finally, a CatBoost [42] classifier is trained. The CatBoost algorithm is a tree-based ensemble classifier, originally an improved and more efficient version of XGBoost that balances the trees better than XGBoost [43]. It is also well-known for constructing trees with categorical feature importance efficiently. Moreover, it uses ordered target encoding and preserves the original state of the feature space. The implementation of symmetric trees by CatBoost distinguishes it from other boosting techniques [43].

After classification, each model generates a decision table for person identification. A decision table holds the score of every user predicted by a machine learning model. The users are ranked according to their scores by each classifier. Next, weighted majority voting, also known as weighted Borda count [31], is used to consider the rank-level scores from each classifier. The primary motivation of using the rank-level fusion is due to its proven popularity and efficacy in scenarios where certain classifiers exhibit higher reliability or accuracy than others [31]. It offers a superior ability to mitigate the effect of underperforming classifiers on the overall ranking, and subsequently, on the final decision. In this study, the individual classifiers showed a wide variance in person identification accuracies. Given this disparity, rank-level fusion was chosen for the ensemble modeling, as it's more adept at handling such variation and mitigating the impact of lower-performing classifiers. The best performing classifier was given the highest weight, while the least effective one received the lowest. The optimized weights for rank-level fusion are calculated using grid-search [38] technique. Finally, from the final decision table, the corresponding highest scorer is selected as the identified user.

IV. EXPERIMENTAL DESIGN

This section delves into the specifics of the materials deployed in the implementation of the proposed methodology, as well as the details of the experimental configuration.

A. DATASETS

Two datasets are used to conduct the experiments to validate the proposed method. The first dataset is used for developing the emotion detection tool, and the second is for the proposed SBB system for person identification.

1) DATASET FOR EMOTION DETECTION

A publicly accessible benchmark dataset [44] is used to train and evaluate an emotion detection modelÂ that extracts the emotion probability scores of six emotion classes from microblogs. The dataset contains over 416K tweets and their corresponding emotion classes: angry, fear, sadness, joy, love, and surprise. The dataset has a balanced mix of all the emotion labels associated in a large number for every emotion class. Therefore, this dataset is chosen to develop the emotion extraction model. The dataset is split into 80:20 for training and testing, following a stratified sampling approach [45].

2) DATASET FOR SBB SYSTEM

For the development and validation of the SBB system based on the proposed emotion-progression method, we have used a proprietary dataset [7] containing fully anonymized tweets of Twitter users. The dataset contains 250 users, with at least 200 tweets in each session per user, collected over a one-year period and organized by four consecutive time segments. The dataset includes mentions, responses, retweets, shared hashtags, shared URLs, timestamps, locations, etc. in addition to the tweets of the users. After feature extraction, the dataset is split into 80:20 for training and testing, using a stratified sample technique [45] and preserving the time progression of tweets.

B. EXPERIMENTAL SETUP

For the implementation of both the emotion detection system and the proposed method for person identification based on human micro-expression, Python version 3.9 is used [46]. The Scikit-learn library is utilized to implement the pipeline of machine learning workflow. A Unix-based operating system, with an Intel Xeon Silver 4210 CPU (40 Cores, 2.2 GHz) with 314GB of memory and an NVIDIA Quadro RTX6000 GPU backend, is used for training and testing. The 5-fold stratified cross-validation technique [47] is used for all experiments. The hyper-parameters are optimized by using grid-search [38]. The optimized parameters of the chosen model–XGBoost–for emotion extraction are: number of estimators is 500, regularization lambda is 0.5, the learning rate is 0.3, and the maximum depth of trees is 5. For the highest performing CatBoost classifier in person identification, the optimal parameters include the number of estimators as 700, the learning rate as 0.18, and the maximum depth of trees as 8. To evaluate both the emotion detection model and the proposed SBB system for person identification, the evaluation metrics such as accuracy, precision, recall, and F1-score are utilized.

V. EXPERIMENTAL RESULTS

The experimental results section is divided into three major categories that include the performance analysis of the emotion detection model, the performance analysis of the proposed method for person identification, and finally, the performance comparison between the proposed method and the original SBB traits.

A. PERFORMANCE ANALYSIS OF EMOTION DETECTION SYSTEM

The first step of the proposed architecture for person identification based on human micro-expression is to develop an emotion detection system that aids in extracting emotion probability scores of six emotion classes from a person's writing samples. Table 1 demonstrates the classification report of different classifiers used for emotion detection.

TABLE 1. Performance of the different classifiers in emotion detection on each of the emotion classes.

Classifier	Emotion	Precision	Recall	F1-score	Accuracy
SVM	Angry	0.88	0.90	0.89	89%
	Fear	0.81	0.85	0.83	
	Love	0.91	0.92	0.92	
	Sadness	0.77	0.74	0.75	
	Joy	0.95	0.93	0.94	
	Surprise	0.73	0.69	0.71	
MNB	Angry	0.89	0.71	0.79	80%
	Fear	0.85	0.64	0.73	
	Love	0.76	0.95	0.84	
	Sadness	0.85	0.41	0.56	
	Joy	0.81	0.92	0.86	
	Surprise	0.86	0.23	0.36	
XGBoost	Angry	0.89	0.92	0.90	**90%**
	Fear	0.83	0.86	0.84	
	Love	0.95	0.91	0.93	
	Sadness	0.76	0.87	0.81	
	Joy	0.96	0.93	0.94	
	Surprise	0.70	0.76	0.73	

The SVM algorithm performs reasonably well in the corresponding emotion detection of a microblog. If we look at the class-wise metrics, most emotion classes demonstrate more than 80% f1-score, and some are even over 90%. An f1-score is the harmonic mean of precision and recall scores that ultimately indicates the overall quality of a model. There are two emotion classes: sadness and surprise, whose f1-score is less than 80%. Nevertheless, the overall class-wise emotion detection performance of SVM is excellent. The MNB algorithm, however, performs significantly worse than other machine learning classifiers. Only two emotion classes have an f1-score of more than 80%, whereas the performance of the rest of the classes is below 80%. While the overall performance is above average, the MNB classifier is not well-fitted because the goal is to extract the emotion probability scores of six emotion classes as correctly as possible. The XGBoost classifier overcomes these class-wise poor detection performances on certain classes produced by both SVM and MNB. In XGBoost, the f1-score of the sadness emotion class is significantly improved to 94%, whereas it is only 75% in SVM. Furthermore, the XGBoost classifier successfully extracts the surprise emotion class with a recall score of 76%, which is 23% in MNB. Finally, in terms of the overall model accuracy for emotion detection, XGBoost performs superior to the others.

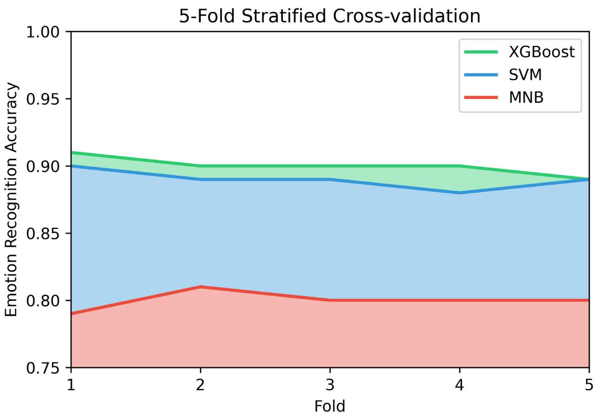


FIGURE 4. 5-fold cross-validation performances of support vector machine, multinomial Naïve Bayes, and XGBoost in emotion detection system.

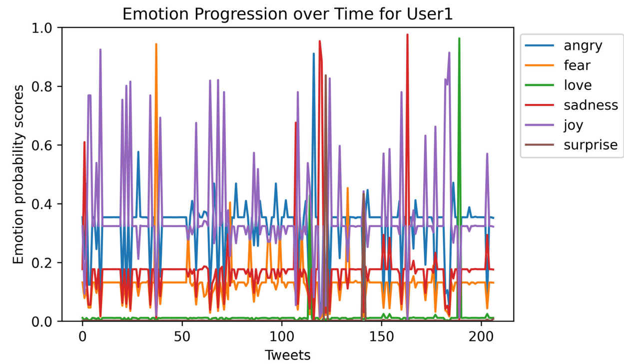
To observe the consistency of the performance throughout the different time segments of the dataset, 5-fold cross-validation is performed for every model. Fig. 4 depicts the 5-fold cross-validation results of each of the classifiers. In every fold, the performance of XGBoost is better than any algorithm at any given fold. The SVM and XGBoost perform similarly; however, the XGBoost outperforms the others with improved class-wise performance result. The average accuracy of SVM and MNB after 5-fold cross-validation is 89% and 80%, respectively. However, the average emotion recognition accuracy of XGBoost is 90%. The standard deviation (σ) of all the classifiers is 0.63.

B. EXPERIMENTAL ANALYSIS OF THE PROPOSED METHOD

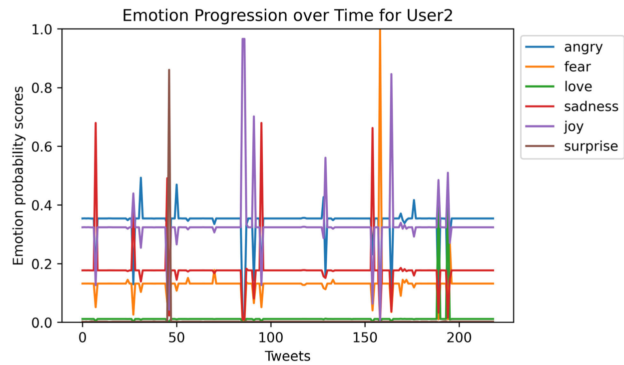
The experiments of the proposed social behavioral biometric: human micro-expression, are divided into two major parts to address the research question set appropriately. In the first set of experiments, we analyze the emotion-progression signals derived from users' microblogs. And then, in the second set of experiments, we analyze and validate the performance of the proposed SBB system which can recognize people based on the innate emotion-progression signals retrieved from their online microblogs.

1) EMOTION-PROGRESSION ANALYSIS OF INDIVIDUALS

The probability scores of six emotion classes are extracted from each microblog of 250 Twitter users using the proposed emotion detection method. The purpose of this experiment is to represent the emotions extracted from users' microblogs as emotion-progression over time, to perform an exploratory emotion signal analysis, and to observe emotion-progressions of different users.



(a) Emotion progression of User1's temporal order of tweets



(b) Emotion progression of User2's temporal order of tweets

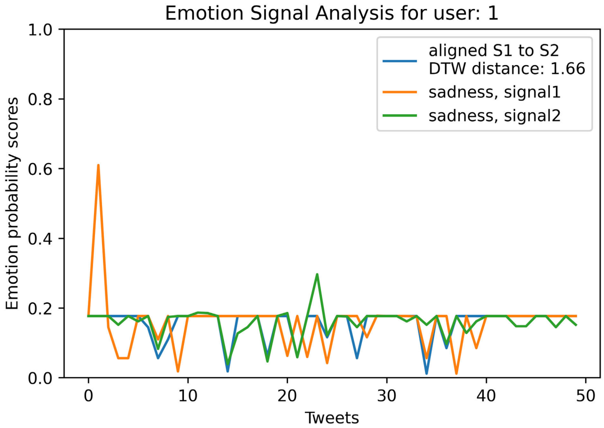
FIGURE 5. Emotion progression over temporal order of tweets, extracted from User1 and User2's available microblogs.

Two randomly selected users' emotion-progressions and the similarity of emotion-progression signals are illustrated in Fig. 5a and 5b.

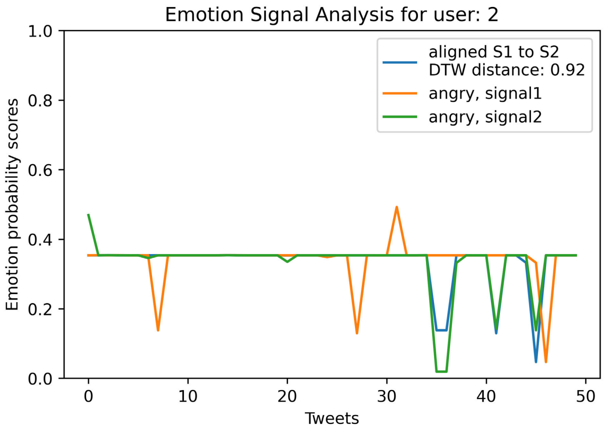
Observing the emotion progression in six emotion classes of an anonymous user 1, the joy emotion class dominates the other emotion classes.

On the other hand, the emotion progression of anonymous user 2 remains flat. For user 2, the angry emotion is consistently higher than the other emotion classes. Thus we observe that the patterns of emotion progressions of the two users are distinctive and different from each other.

Let us now consider some examples of deep-level similarity measurements on user-wise emotion-progression signals. At first, two emotion signals are constructed from the available microblogs and their corresponding emotion probability scores of six emotion classes of a particular user. Fifty microblogs are considered to generate an emotion signal. The DTW algorithm is then applied to the two emotion signals to determine the degree of similarity between them.



(a) Emotion signal analysis of User1



(b) Emotion signal analysis of User2

FIGURE 6. **Emotion-signal similarity analysis of users.**

Fig. 6a and 6b demonstrate the user-specific analysis of emotion signal similarity. For instance, in the sadness emotion progression of user 1 demonstrated in Fig. 6a, the 1^{st} and 50^{th} microblogs are sadness emotion signal 1, and the subsequent 50 microblogs are sadness emotion signal 2; based on the DTW distance score, these signals exhibit similar signal patterns. The lower the DTW distance score, the more similar the signals' patterns. For user 1, the DTW distance score between two sadness signals is 1.66, which is relatively low and indicates that the progression of sad emotion reflects similar patterns. A DTW distance score of 0 indicates that two signals are identical. In user 2, the DTW distance score of angry signal is 0.92. Hence, the analysis of DTW distance metric implies that a pair of emotion signals of a particular emotion class shows similarity if they belong to the same user. The following section of this experiment presents the results of the proposed SBB system for identifying individuals based on their online emotion-progressions.

2) PERFORMANCE ANALYSIS OF PERSON IDENTIFICATION

Three machine learning algorithms, XGBoost [36], Random Forest (RF) [41], and CatBoost [42], are trained using

TABLE 2. **Performance of three classifiers on person identification.**

Classifier	Precision	Recall	F1-score	Accuracy
CatBoost	**0.57**	**0.55**	**0.55**	**55.43%**
Random Forest	0.51	0.52	0.51	52.40%
XGBoost	0.48	0.47	0.47	47.22%

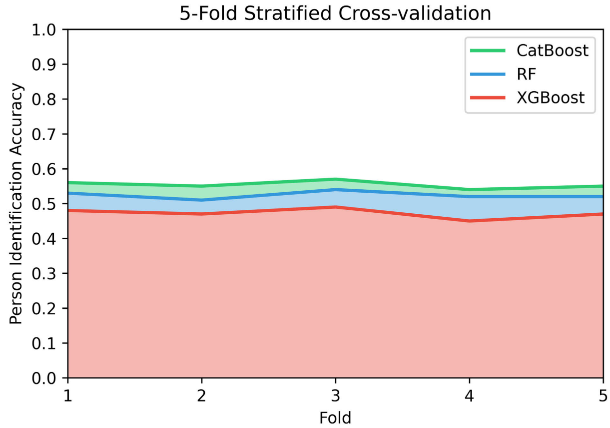


FIGURE 7. **5-Fold cross-validation performances of Random Forest, CatBoost, and XGBoost in person identification.**

the emotion-progression features extracted by utilizing the proposed feature extraction method for person identification. Then a rank-level weighted majority voting technique is applied to improve the performance of person identification. Table 2 presents the person identification results produced by individual machine learning classifiers. Random Forest classifier yields 52.4% detection accuracy over a sample of 250 users. We find that the ensemble of decision trees is a suitable approach to this research problem. During training, the number of available training examples for every user was equal. Therefore, the distribution of samples is well-balanced. The F1-score of Random Forest is 51% which is close to the accuracy score, suggesting that the model training is steady. For XGBoost, however, the performance of the person identification rate is below 50%. The CatBoost classifier outperforms both Random Forest and XGBoost classifiers in terms of its performance in person identification. The accuracy of CatBoost is 55.43% which is about 3% and 8% higher than Random Forest and XGBoost, respectively. The CatBoost classifier performs better feature selection than XGBoost and Random Forest which leads to improved performance [42].

The performance of all the classifiers is cross-validated with a stratified 5-fold cross-validation technique, depicted in Fig. 7. All classifiers retain consistent performance and do not outperform one another in identification accuracy at any stage. The standard deviation (σ) of Random Forest, XGBoost, and CatBoost is 1.01, 1.32, and 1.01, respectively. This experiment also suggests that the proposed method works while shifting the data, as expected. Another critical factor is looking at each classifier's rank-level cumulative identification rate to understand the rank-level learning and decision states. The cumulative matching

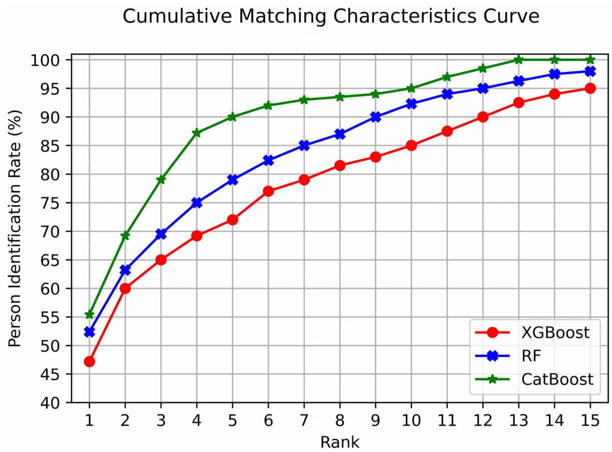


FIGURE 8. Cumulative matching characteristics curve for rank-1 to rank-15 accuracy of XGBoost, CatBoost, and RF in person identification.

TABLE 3. Person identification performance of the proposed method using rank-level weighted majority voting technique.

Classifier	Precision	Recall	F1-score	Accuracy
CatBoost	0.57	0.55	0.55	55.43%
Random Forest	0.51	0.52	0.51	52.40%
XGBoost	0.48	0.47	0.47	47.22%
Ensemble	**0.62**	**0.61**	**0.61**	**61.73%**

characteristics (CMC) curve, illustrated in Fig. 8, is a commonly used evaluation metric in biometric identification systems that represents the cumulative probability of correct identification at or below a rank [48]. The steeper the CMC curve, the better the system's performance because it implies that the correct identification is typically found at a higher rank [48]. The cumulative person identification rate at rank 10 is 95%, 92.5%, and 85% by CatBoost, Random Forest, and XGBoost, respectively. CatBoost, however, reaches to 100% identification accuracy at rank 13. At rank 15, XGBoost and Random Forest achieve a maximum of 98% and 95% accuracy. The most important takeaway from this CMC curve is that a high potential for performance improvement is observed when rank-level weighted probabilities are considered. Furthermore, as the performance is found to be improving steadily, we can identify users 95% of the time within rank 10 and 100% of the time within rank 13. After optimizing the classifiers, rank-level score fusion is applied and an ensemble classifier comprised of Random Forest, CatBoost, and XGBoost is constructed. The result of the rank-level fusion with weighted majority voting is shown in Table 3. According to Table 3, the accuracy of person identification is increased by 4.7% compared to the result of the best classifier. In all precision and recall evaluation metrics, the improvement to the ensemble method is about 5% than the CatBoost classifier. However, it is approximately 8-10% better than Random Forest. The similarity between the f1-score and the person identification accuracy of each model indicates that the model is well-balanced. The f1-score of the ensemble classifier shows 9% and 6% improvement than of Random Forest and CatBoost, respectively. An additional experiment is carried out to investigate the impact of score-level fusion on ensemble modeling's efficacy for person identification. Table 4 demonstrates the comparative person identification performance when rank-level and score-level fusion are applied for ensemble modeling. Despite a slightly lower 60.88% accuracy with score-level fusion, its performance aligns closely with rank-level fusion. Overall, rank-level fusion performed better. Thus, the proposed SBB system with the proposed biometric trait, human micro-expression, achieves 61.73% accuracy with the ensemble classification method.

TABLE 4. Performance comparison between rank-level and score-level fusion for ensemble modeling.

Fusion	Precision	Recall	F1-score	Accuracy
Rank-level	0.62	0.61	0.61	61.73%
Score-level	0.61	0.60	0.60	60.88%

One of the key insights behind the efficacy of the proposed method is due to the approach of embodying the continuity and evolution of an individual's emotions rather than a singular, independent snapshot. While in some cases machine learning approaches perform well, even without any extensive feature engineering, the feature representation technique is the vital part to achieve generalization. The proposed key features are the similarity distances among emotion signals, a novel detail that sets the proposed approach apart from others. In summary, it is clear that the proposed social behavioral biometric addresses the research questions, demonstrating that human micro-expression can be used for person identification.

C. PERFORMANCE COMPARISON OF THE PROPOSED METHOD WITH STATE-OF-THE-ART METHODS

In this subsection, we compare the performance of the proposed method to the performance of original state-of-the-art SBB traits. In order to better reflect and understand where the proposed method stands among the state-of-the-art methods, all the other original SBB traits are re-implemented in this study. The original SBB traits require at least 200 or more tweets as input to identify a person, while the proposed method needs only 100 tweets. Hence, the original SBB traits are re-implemented according to our experimental setup to have a head-to-head comparison of the performance of person identification. The original retweet network, reply network, URL network, hashtag network, and temporal profile of all the available users are generated according to [7] and [25]. Table 5 presents the comparison results of the performance of person identification based on the proposed SBB trait and the original SBB traits. Temporal profile, is found to be the least performing social behavioral biometric with a person identification accuracy of 9.34%. Among the original SBB traits, the reply network is the best-performing SBB trait with an accuracy of 60.74%. The f1-score is low for any SBB trait other than the proposed human micro-expression. This indicates that the proposed human micro-expression

TABLE 5. Performance comparison of the proposed method with the state-of-the-art methods for person identification based on social behavioral biometrics.

SBB Trait	Precision	Recall	F1-score	Accuracy
URL Network	34.85%	37.23%	36.00%	37.57%
Retweet Network	57.09%	58.39%	57.73%	60.74%
Hashtag Network	19.46%	26.65%	22.49%	29.10%
Temporal Profile	6.39%	10.05%	7.81%	9.34%
Reply Network	46.19%	47.67%	46.92%	48.83%
Human micro-expression (Proposed)	**62.14%**	**61.32%**	**61.70%**	**61.73%**

SBB performs well across all evaluation metrics. For the proposed SBB trait, human micro-expression, the scores of precision, recall, and f1-score are consistently higher than the original SBB traits in state-of-the-art. The difference in identification accuracy between the proposed SBB trait and the other SBB traits, excluding Retweet Network, is shown to surpass 12%. From the comprehensive experimentation presented above, the results convincingly establish that the proposed social behavioral biometric, human micro-expression, (1) demonstrates distinctive classifying property among OSN users, (2) can be used for person identification, (3) has a superior distinctive ability for person identification online than the original state-of-the-art SBB traits.

VI. CONCLUSION

In this paper, a novel social behavioral biometric, human micro-expression, is proposed for online person identification. An emotion detection model is developed to extract emotion probability scores of six emotion classes from OSN users' microblogs. To represent the human micro-expression in the form of emotion-progression over time, a novel emotion signal representation method is designed and implemented. After emotion-progression feature extraction, three classical machine learning algorithms are trained to evaluate the proposed method. In the final step, a rank-level fusion technique based on weighted majority voting is applied to improve the performance of person identification.

Experimental results demonstrate that the proposed social behavioral biometric, human micro-expression, demonstrates a strong, distinctive ability for person identification online with a rank-1 accuracy of 61.73%. In addition, the performance of the proposed method surpassed the performance of original state-of-the-art SBB traits. Currently, we are in the process of integrating the proposed human micro-expression feature with features such as URL, retweet, friendship network, and others to investigate if such an integration could enhance the overall identification performance. Fine-tuning transformer-based models for better emotion extraction, which in turn could potentially contribute to increased person identification performance, may lead to further increase in the recognition performance. An effect of selection of different tweet batches for generating emotion signals on the proposed system's performance can also be investigated further. Exploring high-dimensional emotion-progressions can be a new avenue of research for improving the effectiveness of person identification.

REFERENCES

[1] A. K. Jain, P. Flynn, and A. A. Ross, *Handbook of Biometrics*. Cham, Switzerland: Springer, 2007.
[2] S. A. Abdulrahman and B. Alhayani, "A comprehensive survey on the biometric systems based on physiological and behavioural characteristics," *Mater. Today, Proc.*, vol. 80, pp. 2642–2646, Jan. 2023.
[3] Y. Liang, S. Samtani, B. Guo, and Z. Yu, "Behavioral biometrics for continuous authentication in the Internet-of-Things era: An artificial intelligence perspective," *IEEE Internet Things J.*, vol. 7, no. 9, pp. 9128–9143, Sep. 2020.
[4] K. Revett, *Behavioral Biometrics: A Remote Access Approach*. Hoboken, NJ, USA: Wiley, 2008.
[5] M. Sultana, P. P. Paul, and M. Gavrilova, "A concept of social behavioral biometrics: Motivation, current developments, and future trends," in *Proc. Int. Conf. Cyberworlds*, Oct. 2014, pp. 271–278.
[6] M. L. Gavrilova, F. Anzum, A. H. Bari, Y. Bhatia, F. Iffath, Q. Ohi, M. Shopon, and Z. Wahid, "A multifaceted role of biometrics in online security, privacy, and trustworthy decision making," in *Breakthroughs in Digital Biometrics and Forensics*. Cham, Switzerland: Springer, 2022, pp. 303–324.
[7] M. Sultana, P. P. Paul, and M. L. Gavrilova, "User recognition from social behavior in computer-mediated social context," *IEEE Trans. Human-Mach. Syst.*, vol. 47, no. 3, pp. 356–367, Jun. 2017.
[8] S. N. Tumpa and M. Gavrilova, "Linguistic profiles in biometric security system for online user authentication," in *Proc. IEEE Int. Conf. Syst. Man, Cybern. (SMC)*, Oct. 2020, pp. 1033–1038.
[9] M. Sultana, P. P. Paul, and M. L. Gavrilova, "Social behavioral information fusion in multimodal biometrics," *IEEE Trans. Syst. Man, Cybern. Syst.*, vol. 48, no. 12, pp. 2176–2187, Dec. 2018.
[10] Y. Yang, B. Guo, Z. Wang, M. Li, Z. Yu, and X. Zhou, "BehaveSense: Continuous authentication for security-sensitive mobile apps using behavioral biometrics," *Ad Hoc Netw.*, vol. 84, pp. 9–18, Mar. 2019.
[11] S. L. Sahdev, S. Singh, N. Kaur, and L. Siddiqui, "Behavioral biometrics for adaptive authentication in digital banking–guard against flawless privacy," in *Proc. Int. Conf. Innov. Practices Technol. Manage. (ICIPTM)*, Feb. 2021, pp. 261–265.
[12] Z. Chu, S. Gianvecchio, A. Koehl, H. Wang, and S. Jajodia, "Blog or block: Detecting blog bots through behavioral biometrics," *Comput. Netw.*, vol. 57, no. 3, pp. 634–646, Feb. 2013.
[13] A. Awad, "Collective framework for fraud detection using behavioral biometrics," in *Information Security Practices*. Cham, Switzerland: Springer, 2017, pp. 29–37.
[14] J. Granatyr, H. M. Gomes, J. M. Dias, A. M. Paiva, M. A. S. N. Nunes, E. E. Scalabrin, and F. Spak, "Inferring trust using personality aspects extracted from texts," in *Proc. IEEE Int. Conf. Syst. Man Cybern. (SMC)*, Oct. 2019, pp. 3840–3846.
[15] A. Parmentier, R. Cohen, X. Ma, G. Sahu, and Q. Chen, "Personalized multi-faceted trust modeling to determine trust links in social media and its potential for misinformation management," *Int. J. Data Sci. Anal.*, vol. 13, no. 4, pp. 399–425, May 2022.
[16] M. A. Wani, N. Agarwal, and P. Bours, "Sexual-predator detection system based on social behavior biometric (SSB) features," *Proc. Comput. Sci.*, vol. 189, pp. 116–127, Jan. 2021.
[17] Z. Ren, Q. Shen, X. Diao, and H. Xu, "A sentiment-aware deep learning approach for personality detection from text," *Inf. Process. Manage.*, vol. 58, no. 3, May 2021, Art. no. 102532.
[18] S. C. Guntuku, D. B. Yaden, M. L. Kern, L. H. Ungar, and J. C. Eichstaedt, "Detecting depression and mental illness on social media: An integrative review," *Current Opinion Behav. Sci.*, vol. 18, pp. 43–49, Dec. 2017.
[19] M. M. Tadesse, H. Lin, B. Xu, and L. Yang, "Detection of depression-related posts in Reddit social media forum," *IEEE Access*, vol. 7, pp. 44883–44893, 2019.
[20] F. Anjomshoa, M. Aloqaily, B. Kantarci, M. Erol-Kantarci, and S. Schuckers, "Social behaviometrics for personalized devices in the Internet of Things era," *IEEE Access*, vol. 5, pp. 12199–12213, 2017.
[21] M. Sultana, P. P. Paul, and M. Gavrilova, "Social behavioral biometrics: An emerging trend," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 29, no. 8, Dec. 2015, Art. no. 1556013.

[22] R. Dunbar, *How Many Friends Does One Person Need? Dunbar's Number and Other Evolutionary Quirks*. London, U.K.: Faber & Faber, 2010.
[23] B. Gonçalves, N. Perra, and A. Vespignani, "Modeling users' activity on Twitter networks: Validation of Dunbar's number," *PLoS ONE*, vol. 6, no. 8, Aug. 2011, Art. no. e22656.
[24] J. Ramos, "Using TF-IDF to determine word relevance in document queries," in *Proc. 1st Instructional Conf. Mach. Learn.*, vol. 242, no. 1, 2003, pp. 29–48.
[25] M. Sultana and M. Gavrilova, "Temporal pattern in tweeting behavior for persons' identity verification," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2018, pp. 2472–2477.
[26] P. Kumar and M. L. Gavrilova, "Latent personality traits assessment from social network activity using contextual language embedding," *IEEE Trans. Computat. Social Syst.*, vol. 9, no. 2, pp. 638–649, Apr. 2022.
[27] C. Suero Montero, M. Munezero, and T. Kakkonen, "Investigating the role of emotion-based features in author gender classification of text," in *Proc. Int. Conf. Intell. Text Process. Comput. Linguistics*. Cham, Switzerland: Springer, 2014, pp. 98–114.
[28] C. Liu, F. Li, and L. Li, "Research on gender prediction for social media user profiling by machine learning method," in *Proc. Int. Conf. Commun., Inf. Syst. Comput. Eng. (CISCE)*, May 2021, pp. 831–836.
[29] M. A. Wani, P. Bours, N. Agarwal, and S. Jabin, "Emotion-based mining for gender prediction in online social networks," in *Proc. ACM, Int. Conf. Mach. Learn. Data Sci.*, 2019, pp. 1–9.
[30] D. J. Berndt and J. Clifford, "Using dynamic time warping to find patterns in time series," in *Proc. KDD Workshop*, vol. 10, no. 16, 1994, pp. 359–370.
[31] S. Z. Li, *Encyclopedia Biometrics: I-Z*, vol. 2. Cham, Switzerland: Springer, 2009.
[32] C. G. Patil and S. S. Patil, "Use of Porter stemming algorithm and SVM for emotion extraction from news headlines," *Int. J. Electron., Commun. Soft Comput. Sci. Eng.*, vol. 2, no. 7, p. 9, 2013.
[33] A. Seyeditabari, N. Tabari, and W. Zadrozny, "Emotion detection in text: A review," 2018, *arXiv:1806.00674*.
[34] P. Nandwani and R. Verma, "A review on sentiment analysis and emotion detection from text," *Social Netw. Anal. Mining*, vol. 11, no. 1, pp. 1–19, Dec. 2021.
[35] W. S. Noble, "What is a support vector machine?" *Nature Biotechnol.*, vol. 24, no. 12, pp. 1565–1567, Dec. 2006.
[36] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2016, pp. 785–794.
[37] A. M. Kibriya, E. Frank, B. Pfahringer, and G. Holmes, "Multinomial naive Bayes for text categorization revisited," in *Proc. Australas. Joint Conf. Artif. Intell.* Cham, Switzerland: Springer, 2004, pp. 488–499.
[38] P. Liashchynskyi and P. Liashchynskyi, "Grid search, random search, genetic algorithm: A big comparison for NAS," 2019, *arXiv:1912.06059*.
[39] H. Wielandt, *Finite Permutation Groups*. New York, NY, USA: Academic, 2014.
[40] P. Senin, "Dynamic time warping algorithm review," Inf. Comput. Sci. Dept. Univ. Hawaii, Manoa Honolulu, HI, USA, Tech. Rep. CSDL-08-04, 2008, p. 40, vol. 855, nos. 1–23.
[41] G. Biau and E. Scornet, "A random forest guided tour," *TEST*, vol. 25, no. 2, pp. 197–227, Jun. 2016.
[42] J. T. Hancock and T. M. Khoshgoftaar, "CatBoost for big data: An interdisciplinary review," *J. Big Data*, vol. 7, no. 1, pp. 1–45, Dec. 2020.
[43] L. Prokhorenkova, G. Gusev, A. Vorobev, A. V. Dorogush, and A. Gulin, "CatBoost: Unbiased boosting with categorical features," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 31, 2018, pp. 6639–6649.
[44] E. Saravia, H.-C.-T. Liu, Y.-H. Huang, J. Wu, and Y.-S. Chen, "CARER: Contextualized affect representations for emotion recognition," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, 2018, pp. 3687–3697.
[45] V. L. Parsons, "Stratified sampling," *Wiley StatsRef, Statist. Reference Online*, pp. 1–11, Feb. 2017, doi: 10.1002/9781118445112.stat05999.pub2.
[46] M. Lutz, *Programming Python*. Sebastopol, CA, USA: O'Reilly Media, 2001.
[47] P. Refaeilzadeh, L. Tang, H. Liu, L. Angeles, and C. D. Scientist, "Cross-validation," *Encyclopedia Database Syst.*, vol. 5, pp. 532–538, Jan. 2020.
[48] N. Damer, A. Opel, and A. Nouak, "CMC curve properties and biometric source weighting in multi-biometric score-level fusion," in *Proc. 17th Int. Conf. Inf. Fusion (FUSION)*, Jul. 2014, pp. 1–6.

ZAMAN WAHID is currently pursuing the M.Sc. degree in computer science with the University of Calgary. He is also affiliated with the Biometric Technologies Laboratory as a Graduate Research Assistant. He is an aspiring researcher in the field of applied AI, machine learning, and deep learning. He has around three years of professional experience within the domain of software engineering across startup, national, and multinational companies, including United Nations. He has several previous research publications in reputed journals and conferences within the research field. He was a recipient of the 2022 Alberta Graduate Excellence Award by the Government of Alberta, Canada. In previous years, he was selected as one of the Youngest Global Talents across the world for 2018 Unleash Innovation Laboratory Program, National University of Singapore; and one of the 20 student leaders from all over the commonwealth countries by the Association of Commonwealth Universities (ACU) for 2017 ACU Residential School Program, Heriot-Watt University Malaysia. In 2019, he was recognized by the Indian High Commission and Ministry of Youth and Affairs, Government of India, as one of the 100 most prolific young professionals in Bangladesh for 2019 Bangladesh Youth Delegation Team to India Program and featured in *Bharat Bichitra*, a renowned Indian monthly magazine.

ASM HOSSAIN BARI received the B.Sc. degree in computer science and information technology from the Islamic University of Technology, in 2010, and the M.Sc. degree in computer science from the University of Calgary, Canada, in 2020, under the supervision of Prof. Marina L. Gavrilova. He was with the Samsung Research and Development Institute Bangladesh (SRBD), from November 2010 to August 2018. He has authored over 15 international journals and conference papers. He has secured U.S. Patents while working in SRBD. His research interests include behavioral biometrics, computer vision, and machine learning.

FAHIM ANZUM (Graduate Student Member, IEEE) received the M.Sc. degree in computer science from the University of Calgary (uCalgary), Calgary, AB, Canada, in 2021, under the supervision of Dr. Mario Costa Sousa and Dr. Usman Alim, where he is currently pursuing the Ph.D. degree in computer science, under the supervision of Dr. Marina Gavrilova. During his master's study, he was with Suncor Energy Inc., as a Research Intern. Before joining uCalgary, he was with the Computer Science and Engineering (CSE) Department, United International University (UIU), Bangladesh, as a Lecturer. His research interests include the application of machine learning (ML) and deep learning (DL) in various areas, such as online social network analysis, natural language processing, and data mining.

MARINA L. GAVRILOVA (Senior Member, IEEE) is currently a Full Professor with the University of Calgary. She is an international expert in the area of biometric security, machine learning, pattern recognition, and information fusion. She directs the Biometric Technologies Laboratory. She has published over 300 books, conference proceedings, and peer-reviewed articles. Her professional excellence was recognized by the Canada Foundation for Innovation, the Killiam Foundation, the U Make a Difference Award, and the Order of the University of Calgary. She is the Founding Editor-in-Chief of *Transactions on Computational Sciences* (Springer), and serves on the editorial boards for the IEEE Transactions on Computational Social Sciences, IEEE Access, *The Visual Computer*, *Sensors*, and the *International Journal of Biometrics*.