Detecting User Credibility on Twitter using a Hybrid Machine Learning Model of Features' Selection and Weighting

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***Abstract*—With the pervasive and rapidly growing presence of the internet and social media, creating untrustworthy accounts has become effortless, allowing fake news to be spread for personal or private interests. As a result, it is crucial in this era to investigate the credibility of users on social networking platforms such as Twitter. In this research, we aim to integrate existing solutions from previous research to create a hybrid model. Our approach is based on selecting and weighting features using supervised machine learning methods such as ExtraTressClarifier, correlation-based algorithm methods, and SelectKBest to extract new ranked and weighted features in the dataset and then use them to train our model to discover their impact on the accuracy of user credibility detection issues. The research objective is to combine feature selection and weighting methods with Supervised Machine Learning to evaluate their impact on the accuracy of user credibility detection on Twitter. In addition, we measure the effectiveness of different feature categories on this detection. Experiments are conducted on one of the online available datasets. We seek to employ extracted features from a user's profile and statistical and emotional information. Then, the experimental results are compared to discover the effectiveness of the proposed solution. This study focuses on revealing the credibility of Twitter (or X-platform as recently renamed) accounts, which may result in the need for some adjustments to the generalization of Twitter's outputs to other social media accounts such as LinkedIn, Facebook, and others.**

***Keywords*—User credibility; supervised machine learning; feature selection; feature weighting; social network; twitter**

I. Introduction

Recognizing reliable sources of information within online social networks (OSNs) poses a significant challenge, requiring a solution to differentiate between credible and non-credible users. Ensuring this is vital for reducing the spread of misinformation and fake news, as well as minimizing their harmful consequences [1][9]. Twitter stands as a key information hub in our region, attracting individuals from various age groups and professional backgrounds [2] [3], as its audience accounted for over 335 million monthly active users worldwide by January 2024 [4]. In the Kingdom of Saudi Arabia alone there are at least 11.4 million active users [5]. Therefore, detecting uncredible Twitter users is of special importance for countering the spread of misinformation in our communities.

Numerous studies have employed machine learning (ML) for Twitter User Credibility Detection (TUCD), treating it as a classification problem where user features are often treated uniformly. The challenge arises in handling high-dimensional datasets, exacerbated by irrelevant and redundant attributes, potentially compromising performance and yielding suboptimal results. The accuracy of user-credibility detection hinges on the features' quality in the classification process [6]. However, not all features contribute equally to accurate predictions, necessitating the identification and weighting of features' importance scores. Various techniques, including SelectKBest, ExtraTrees-Classifier, Principal Component Analysis (PCA), and Mutual Information, are available for feature selection and weighting. Yet, the clarity regarding the efficacy of detecting user credibility by them is still uncertain [7] [8]. This study represents an extension of our previous research, which confirmed the positive effect of selecting features to improve the accuracy of TUCD [9]. As well as the positive effect in most cases of weighing those features on the same issue [10]. This paper combined both previous methods to create a hybrid model. It aims to evaluate the impact of the proposed method on user credibility detection performance through the implementation of Supervised Machine Learning (SML) experiments. Additionally, the study explores different categories of features and their combinations in this context.

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II. Research Background

User credibility is crucial in online social networks (OSNs), since it defines the trustworthiness of individuals as information sources. Within OSNs like social media, where content creation and opinion expression are unrestricted, credibility is multifaceted, encompassing qualities that establish trust [11] [12] [13]. Detecting user credibility (UCD) involves assessing various features to differentiate between credible and non-credible users. These features include content-based aspects such as quality and relevance, interaction-based factors like user engagement, profile-based demographics, and sentiment-based indicators [14] [15] [16] [17] [18] [19]. Machine learning algorithms play a pivotal role in quantitatively analyzing these features, thereby enhancing online communication quality and reliability.

Supervised Machine Learning (SML) forms the backbone of UCD methodologies, offering automatic learning and decision-making from trained data [13]. Techniques like decision tree (DT), logistic regression (LR), naive Bayes (NB), random forest (RF), and support vector machine (SVM) are commonly employed for UCD tasks [16] [19] [20] [21] [22] [23] [24] [25] [26] [27]. These techniques serve classification tasks, differentiating between credible and uncredible users by identifying unique features. Moreover, boosting algorithms like Adaptive Boosting (AdaBoost) and Gradient Boosting (GB) have evolved [27], with XGBoost (XGB) emerging as a powerful algorithm, integrating regularization to control model complexity and resist overfitting.

Feature engineering, a pivotal aspect of machine learning pipelines, transforms raw data into features, significantly impacting model accuracy [28] [29] [30]. It addresses challenges like noise reduction, handling missing data, and preventing overfitting. Feature engineering processes involve feature creation, transformation, extraction, and selection [31]. Feature selection techniques encompass supervised methods like filter, wrapper, and embedded approaches, prioritizing relevant features for UCD tasks [32] [33] [34] [35]. Popular methods include Recursive Feature Elimination (RFE), SelectKBest, Principal Component Analysis (PCA), and Mutual Information [30] [36] [37].

Feature weighting methods are essential for assessing the importance of features within datasets. Techniques like the Analytic Hierarchy Process (AHP), information gain ratio, chi-squared test, and extra tree classifier enable the determination of feature weights. AHP facilitates effective feature weighting, enhancing model performance across various applications. The information gain ratio proves beneficial for high-dimensional feature spaces, while the chi-squared test assesses significant associations between categorical features and target variables [38] [39] [40] [41] [42].

Several datasets are available for UCD research, providing valuable resources for model training and evaluation. Datasets like CredBank [43], FakeNewsNet [44], ArPFN [45] and PHEME [46] offer diverse collections of tweets and user information, categorized based on credibility ratings or association with fake news. These datasets serve as learning sets for evaluating different machine learning models' performance in UCD tasks, contributing to advancements in the field. Comparisons of dataset characteristics aid researchers in selecting appropriate datasets for their specific UCD investigations.

III. Literature Review

The assessment of information credibility within OSNs heavily relies on the trustworthiness of its sources, particularly when dealing with data from unknown individuals lacking established credibility indicators. Consequently, a significant volume of scientific research has emerged to address the challenge of automated User Credibility Detection (UCD). A query on the Google Scholar database using terms associated with "detecting user credibility across platforms" from 2015 to 2023 returned 17,300 relevant articles, highlighting the significant interest this subject has garnered.. In this review, we focus on discussing studies that are most relevant to our research.

A plethora of techniques has been employed for UCD on OSNs, with many studies utilizing machine learning methods such as Support Vector Machines (SVMs) [47] [14] [48] [49] [50] [51] [52], Naïve Bayes (NB) [50], Random Forest (RF) [16] [19] [53] [54] [55] [56], XGBoost [2] [57] [58] [59], Logistic Regression (LR), [58] [60] [61]and Decision Trees (DT) [13] [14] [62] [63], or they adopt an ensemble model [56] [63]. Moreover, a hybrid approach combining SML with other techniques has been widely proposed. These techniques include the utilization of graph-based approaches, as presented by [48], where researchers analyze the credibility of customers using a twin-bipartite graph to model the relationships among users, products, and shops (PCS graph). They then calculate the scores of products/shops and the credibility of customers interactively using iteration algorithms. In the same context, [61] employs node2vec to derive features from the Twitter followers/following graph, combining user features from Twitter and the associated social graph. Meanwhile, [5] introduces the CredRank algorithm, which calculates user credibility in OSNs by analyzing user behavior where authors grouped users based on behavioral similarities. The author in [64] presents the UCred (User Credibility) model, a fusion of machine learning and deep learning methods like RoBERT (Robustly optimized BERT), Bi-LSTM (Bidirectional LSTM), and RF (Random Forest), with the output integrated into a voting classifier for improved TUCD accuracy. Another hybrid strategy proposed by [57] integrates sentiment analysis with a social network to identify features applicable to TUCD. This approach incorporates sentiment scores from user historical data and employs a reputation-based method for individual user profiles. While [56] delves into reputation features through a probabilistic reputation feature model, showing enhanced performance compared to raw reputation features, particularly in overall accuracy for detecting users' trust in OSNs. Additionally, [58] introduces domain-based analysis of user content by combining semantic and sentiment analyses to estimate and predict user domain-based credibility in social big data. Finally [50] evaluates the credibility of user profiles and content using sentiment analysis and machine learning.

Furthermore, various classification schemes have been proposed for UCD, including binary classification [24] [35] [56] [65], or it can take the form of a scale measurement, as [12] proposed in their research that provides the CredRank algorithm, which measures the credibility of users in OSNs based on their online behavior. Moreover, [61] we assigned a probability to each user, indicating their likelihood of spreading fake news. Alternatively, it can take the form of multiple values, such as those presented in [2] and [66], wherein [66], the users' credibility scores range from 0 to 12, where 0 means that the user does not say the truth. The more truthful tweets he posts, the more his credibility score increases. This study provides the user score, tweet score, and a message describing the tweet as overall true, false, or unable to verify. In the same context, [2] assigned three values to user credulity, which can be either credible, non-credible, or undecidable. In another classification presented in [67], the authors developed a mathematical model to predict the popularity of news. In their model, they classified users into four main types: neutral, active, suspicious, and non-responding. The author in [68] introduced the user credibility index (UCI) to identify trustworthy Twitter users by integrating four interrelated components: reputation-based component, credibility classifier engine, user experience component, and feature-ranking algorithm. These components collaborate algorithmically to evaluate the credibility of both Twitter users and their tweets.

Feature engineering involves the conversion of raw data into appropriate features for machine learning models. In other words, it is the process of selecting, extracting, and transforming the most related features from the available data to construct more accurate and efficient machine learning models [69]. Feature engineering has emerged as a crucial aspect of UCD, with researchers employing techniques such as creating new features, feature selection, and feature weighting to enhance model efficiency and performance.

The creation of new features from existing ones was used in [16] [17] [52] [55] [70]. It is used to facilitate distinguishing between spammers and real reviewers in online reviews [70] or to detect bot accounts on Twitter [52]. The author in [16] used new features to discover false news on Twitter by calculating the Twitter account age and verifying the number of this account's followers, friends, and statuses to detect fake accounts. Additionally, they created the favorite count feature that has been used to determine the activity of the account, which they claimed could be a sign of a fake account. On the same page, [17] identified credible Twitter users by focusing on users' information related to their field of competence by providing additional features such as favorites, number of tweets, user education status, and the sentiment reflected in their tweets. They also investigated the impact of adding different combinations of features on the accuracy of the TUCD model. The authors in [55] detected tweet credibility using the IBM Watson natural language understanding tool to calculate sentiment and emotion features and employed the IBM meaning cloud tool for tweet polarity calculation. However, well-engineered features can assist in avoiding overfitting and reducing the training time and cost by providing less complex algorithms that are faster to run and easier to maintain [6].

Working with a large number of features is a complex task that emphasizes the role of feature selection which reduces the dimensionality of the dataset and identifies the features that best suit the classification process [53]. Several studies [2] [16] [19] [42] [53] [54] [55] [62] [63] [65] [71] [72] [73] [74] have employed different feature selection methods to focus on the most relevant and important features to be involved in their prediction, as well as to lower the required computational processes. The authors in [19] [42] and [74] used correlation-based feature selection methods. In [19], this method was employed to decrease the number of features from 34 to 7, which are the features that affect their detection method for classifying a Facebook user as credible. However, [42] the correlation among the features was found to determine the most discriminatory feature for user credibility classification. They then excluded these features because they served as outliers and were biased. In addition, they notice some features that are equally distributed between credible and non-credible users; therefore, these features are discarded because they do not add any value to the classification. In [74], the credibility of Twitter users in the stock market was evaluated by assessing the correlation between each user's credibility and their social interaction features. Additionally, [71] employed the Extra-Trees classifier to eliminate irrelevant features for diagnosing breast cancer, revealing that the top three features—glucose levels, age, and resistance results—maximized model accuracies. Another study [16] focused on detecting false news on Twitter, utilizing the k-best method for selecting the final feature set. In contrast, [65] employed five feature selection methods to enhance spam detection. Furthermore, [72] introduced a dynamic feature selection method by clustering similar Twitter users using the K-Means algorithm and using different features for each user group, rather than a static set of features for spam classification. Authors of [53] addressed spammer detection with a hybrid approach combining logistic regression and principal component analysis (LR-PCA) for dimensional reduction, claiming increased classification accuracy. On the other hand, [73] used recursive feature elimination (RFE) to evaluate optimal features for improved spam detection accuracy, selecting the top 10 features from 31. Whilst [54] examined the best features identified by the random forest algorithm, achieving over 90% accuracy in detecting online bots on Twitter. In the same context, [62] utilized a light gradient-boosting machine (light-GBM) model to evaluate feature importance, dropping features based on their importance. The author in [2] adapted a binary variant of the hybrid Harris Hawk algorithm (HHO) to identify the credibility of Arabic tweets through the elimination of irrelevant or redundant features. However, researchers in [63] employed an ant colony optimization (ACO) algorithm for feature selection, reducing the number of features from 18 to 5 to classify OSN content as credible or fake. This feature selection method provided a significant improvement in the classification accuracy, as stated by the authors. In addition, to better classify the credibility of the posted content on Twitter, [55] we used both a mean decrease accuracy graph that tests how the model performs in the case of removing a particular variable and a mean decrease Gini graph that measures the purity of leaves without each variable to select the top 10 features out of their 26 features based on user, content, polarity, emotion and sentiment characteristics, and determined that sentiment and polarity of tweets represent the most important variables in determining tweet credibility. Overall, these studies showcase diverse feature selection methods applied to different domains, aiming to enhance model performance and accuracy concluding that a good feature set that contains many independent features that are highly correlated with the result can significantly facilitate the learning process [6].

Feature weighting has been addressed in several studies. In [19], the authors suggest a credibility formula for Facebook users. This formula consists of parameters, each of which is multiplied by a specific weight. These weights were computed according to the analytical hierarchical process (AHP) approach, which depends on credibility theory. By applying this formula, user accounts were ranked according to their credibility ranking. Accordingly, they predicted the degree of trust and credibility of Facebook users. In the same context, [75] they created an updated form (AHP) called the "Interval Type-2 Fuzzy Analytical Hierarchy Process" for ranking online reviewers in terms of credibility in their study that addressed the reviewer credibility problem. Moreover, [76] proposed a model that analyzes the credibility of publications on information sources in several social networks; the credibility analysis is based on three measures, text credibility, user credibility, and social credibility. Another study [77] calculated a user credibility score using opinion mining to detect fake news. In their research, the user credibility is calculated based on user reputation, user influence, and user comments. Each has a particular weight, where the user comments have a lower weight of (0.2), as it does not directly reflect the credibility of a user. The reputation and influence of users on social media have the same weight as (0.4) because they easily show the user's credibility. The CredRank was proposed in [12]. It measures user credibility by finding similarities among their online behaviors. The purpose of this algorithm is to identify coordinated behavior on social media and allocate a reduced credibility weight to users involved in such coordinated activities. Coordinated users can easily repress other users and prohibit their content from spreading on social media. Additionally, they are capable of spreading misleading information. In the same context, [78] we assigned weights to different feature items using the information entropy method. They took into account four aspects (strength of social relationships, extent of social influence, value of information, and control of information transmission) to formulate a model for evaluating user credibility. However, defining the best weights remains an open problem that must be solved [6].

Studies related to TUCD have investigated various features. In [65], authors utilized various publicly available language-independent features extracted from four distinct languages to tackle the characteristics and nature of spam profiles on a social network like Twitter, aiming to improve spam detection. The author in [57] proposed a new probabilistic reputation[1] feature model. Reputation was also addressed by [18], where the authors in [18] analyzed the user’s reputation on a given topic within the social network and analyzed the user’s profile and his or her sentiment to identify topically relevant and credible sources of information. This study [47] introduces a credibility rating method to visualize the credibility of Twitter user profiles by using profile, images, links, content, and sentiment features. In their research, [13] several key features of tweets impact their credibility, including the user's spending time on Twitter, his or her post frequency, friends/followers' counters, and the number of retweets his or her tweets received. Focusing on tweets related to eight different events, [79] it was found that credibility was most intensely associated with the inclusion of URLs, mentions, retweets, and tweet length. The author in [80] observed that users rely on easily identifiable information, such as usernames and profile pictures, to form their perceptions of credibility. Other research calculated users' credibility scores [56] based on users' social profiles, content credibility, number of retweets and likes, and the sentiment scores. Their assertion was that a higher user credibility score was indicative of increased influence and trustworthiness. TUCD has also been addressed by, [81] in which the authors depended on sentiment features, the existence of hashtags, emojis, and biased in users' tweets played a crucial role in the detection process. Conversely, [64] asserted that features like the user's number of followers, the quantity of produced tweets, and the ratio of tweet number to account creation length in days influence credibility level, while the number of followers has the most pronounced effect.

Overall, the literature review underscores the diversity of techniques and approaches employed in UCD, reflecting the complexity of assessing user credibility in OSNs. These studies provide valuable insights and methodologies for enhancing the accuracy and reliability of UCD systems across different platforms and domains. However, it should be noted that despite extensive work in this area, some of the specific factors addressed in this research including combining feature selection with feature weighting in addition to examining different feature categories have not been comprehensively explored in previous studies.

[1] Reputation is indirect information like information from third party witnesses.

IV. Materials and Method

This section provides an overview of the methodology adopted in the study as an expansion of our work in [9] and [10]. Different embedded methods, such as the ExtraTreeClassifier, SelectKBest, and mutual information, are incorporated for feature engineering, either by transforming them to weighted features or by selecting the most impacting feature. It is performed midway between feature extraction and classification. Feature engineering is the process of automatically identifying more efficient features, which will contribute to improving prediction results. The processing of irrelevant features or equal processing of all features decreases the accuracy of the model. Also, feature selection may reduce the execution time for classification. Fig. 1 shows the main stages of the research methodology.

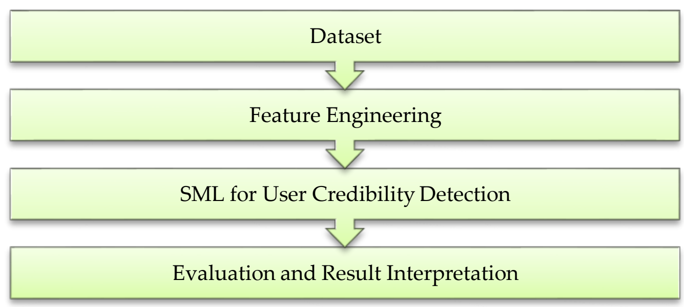

Fig. 1. Research stages

A. Dataset

Our experiments were conducted on the ArPFN dataset [45] which is the most recent dataset that was conducted in (2022) and includes the largest number of features. The ArPFN [45] is a real dataset constructed using three primary stages. First, verified Arabic claims were compiled from diverse sources. These claims were then employed to identify the tweets disseminating them. Finally, the users correlated to these tweets were pinpointed and classified according to their inclination to propagate fake news, as discerned from the frequency of their tweets. The ArPFN dataset encompasses 1546 user accounts on Twitter. Among these, 541 users are inclined to spread fake news (non-credible), while 1005 users are not inclined to spread fake news (credible).

As seen in Table I, the dataset comprises three different types of features for each user: the profile, which includes 11 features; the emotional type, which includes 11 features; and the statistical type, which consists of 17 features. In total, 39 features for each user were ready for use in the dataset.

TABLE I. ArPFN Feature Types [45] [9] [10]

Feature Type	Number of Features	Description
Profile	17	Includes: identification information, verification status, follower counts, following counts, and user's tweets frequencies.
Emotional	11	Includes: trust, anger, sadness, anticipation, disgust, love, fear, joy, , optimism, surprise and pessimism..
Statistical	11	Characterize the users' influence and activities by examining metrics such as the proportion of user tweets containing hashtags, the average number of hashtags/tweet, the proportion of user tweets that are replies, the proportion of user tweets with URLs or media (such as images or videos), retweets counts.

B. Feature Engineering

This phase focuses on identifying the relevant features and estimating their importance in UCD. Each category of features undergoes individual processing and is subsequently merged with the other types, leading to the creation of seven distinct feature sets, as outlined below:

Datasets: { (profile), (emotional), (statistical), (profile + emotional), (emotional + statistical), (profile +statistical), (profile+emotional+ statistical)}.

Different alternatives will be taken into account with each set during this phase.

1) First, all raw data will be considered as the first alternative.

2) Second, feature selection methods are applied to select various sets of features based on their importance employing machine learning methods such as SelectKBest, and correlation. This approach consists of the following steps:

a) Applying a selection method to determine important scores.

b) Arranging features in descending order based on their significance.

c) Removing the lower (50%) of features with the least importance.

3) The third method is the feature-weighting method. To assign weights to features, we explored machine learning weighting estimator methods, including ExtraTree-Classifier and principal component analysis (PCA). This approach encompasses the subsequent steps:

a) Calculating the weights for all features using ML weighting methods.

b) Extracting the weighted features by Multiplying each feature value by its weight.

4) The last alternative is selecting the most important element of the weighted features, which combines alternatives 2 and 3 simultaneously.

C. User Credibility Detection

This phase of the proposed research will focus on designing and developing a machine-learning model with the capability to differentiate between credible and non-credible users on Twitter. The rationale for selecting a machine-learning algorithm for a user-credibility detection system was informed by the results of the literature review, particularly the finding that machine learning has achieved highly accurate outcomes in classification problems.

To obtain a more effective and generalized model, we aim to train the model 10-fold. K-fold cross-validation was used to reduce overfitting. Subsequently, to identify the most accurate classifier for our feature sets, the most commonly used classification algorithms, such as XGBoost, SVM, and LR, were applied and compared to each other.

D. Evaluation and Results Interpretation

We aim to use Python for model implementation and benefit from its wide range of available open-source libraries such as Sciti-learn and Matplotlib. Once the proposed system is developed, testing and evaluation will be conducted to address any limitations. In this phase, each alternative from the previous phase underwent validation using various evaluation metrics, encompassing accuracy, precision, recall, and F-score.

The results were then analyzed and visualized using Python library visualization tools, such as bar plots, heatmaps, and confusion matrix visualization. Fig. 2 shows the flow diagram of the proposed model.

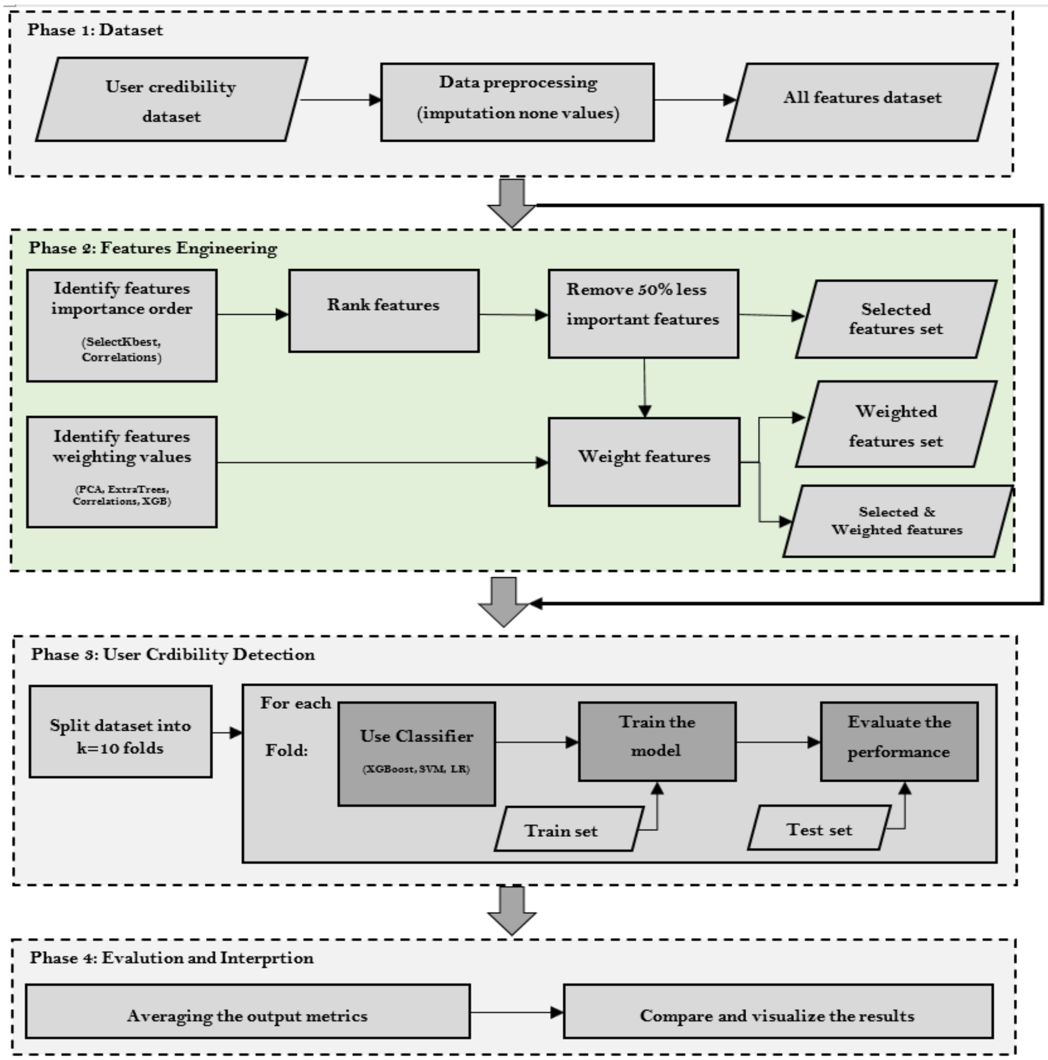

Fig. 2. Flow diagram of the proposed model

V. RESULTS

The application of the proposed methodology yielded valuable results for assessing the impact of different feature engineering methods on the accuracy of TUCD. These findings can be reviewed as follows:

A. Feature Selection

Feature selection entails the identification and removal of irrelevant and redundant information to reduce data dimensionality. In [9], the balance between efficacy and interpretability was carefully considered. The choice of SelectKBest and correlation-based algorithms in this context stems from their specific merits. SelectKBest is valued for its simplicity and efficiency in selecting the top k features through statistical tests, offering a straightforward method for feature selection, this approach enables us to pinpoint the most informative features while keeping computational complexity to a minimum. On the other hand, correlation-based algorithms are selected for their ability to capture relationships and dependencies between features. By evaluating the correlation between each feature and the target variable, we can prioritize features that demonstrate the strongest connections with user credibility. This nuanced approach has empowered us to unveil intricate patterns within the data. These Two methods were applied in this study as follows.

1) SelectKBest: In our approach, we employed Scikit Learn's SelectKBest to identify the k-best features for the model. This algorithm utilizes a score classification function to assess the relationship between the explanatory variable (x) and the explained variable (y), ultimately returning the highest K scores corresponding to the features. When implementing the SelectKBest algorithm on a dataset, it is crucial to specify the value of K. Our experiments revealed that selecting a K value exceeding 50% of the total number of features in the dataset results in a different set of features each time, potentially influencing the accuracy of the final outcome. Therefore, careful consideration of the K value is essential to ensure consistency and reliability in feature selection.

2) Correlation-based algorithms: The correlation measure offers a direct filtering mechanism that arranges features by employing a heuristic evaluation function dependent on correlation. This evaluation function orders features that display significant correlations with the target class while reducing inter-feature correlations. Features that show little correlation with the class were considered insignificant and consequently omitted from the analysis.

3) Selection methods results: The outcome of applying feature selection methods on our datasets confirmed that these techniques are effective for improving TUC detection accuracy, as shown in Table II and Fig. 3.

TABLE II. FEATURE SELECTION METHODS [9]

Dataset Category	Accuracy of All Features	Accuracy of Selected Features	
		Correlation	Select K-Best
Profile	0.526	0.630	0.622
Emotional	0.505	0.624	0.603
Statistical	0.501	0.665	0.603
Profile and Emotional	0.530	0.657	0.620
Profile and Statistical	0.543	0.665	0.630
Emotional and Statistical	0.522	0.638	0.616
Profile, Emotional, and Statistical	0.523	0.723	0.671

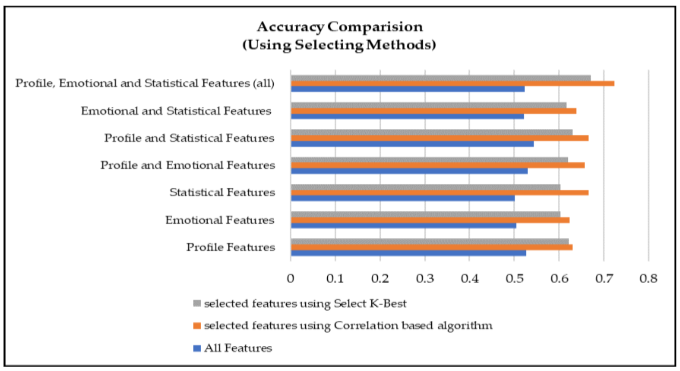

Fig. 3. Feature selection

B. Feature Weighting

Weighing features according to their importance in predicting the correct classification has been addressed by several machine learning algorithms. It is crucial to highlight that feature-weighting algorithms do not inherently reduce the dimensionality of the data. Unless features with very low weights are deliberately excluded from the dataset at the outset, the assumption is that each feature bears some level of importance for the induction process, and the degree of significance is reflected by the magnitude of its weight. In [10], we examined three of the most widely used methods to calculate the importance of features, employing the following approaches:

4) Correlation coefficients: Examining the model's correlation coefficients using a logistic regression algorithm, a large value of the coefficients (negative or positive) indicates the feature's influence on the detection of TUC, while a zero coefficient means that the feature does not have any impact on the detection.

5) Tree-based: Training the tree-based model to access the feature importance, we used ExtraTreeClssifier and XGBClassifier to obtain each feature's importance.

6) Principal Component Analysis (PCA): Used to determine variance in the dataset. We used the first principal component (PC1) to define the importance of the features in the datasets.

7) Weighting methods results: The aforementioned methods were employed on the datasets within our model. As demonstrated in Table III and Fig. 4, the results indicated that under the best-case scenario, five out of seven groups exhibited positive effects when applying feature weighting (using the ExtraTree-Classifier) to enhance the accuracy of TUCD.

TABLE III. WEIGHTING METHODS [10]

Dataset Category	*No weighting*	*Weighting Methods*			
		Extra Tree-Classifier	*Corr-Coefficient*	*XGB*	*PCA*
Profile	**0.526**	0.503	0.515	0.521	0.501
Emotional	0.505	0.518	0.515	0.508	0.516
Statistical	0.501	0.524	0.524	0.480	0.496
Profile and Features	0.530	**0.546**	0.524	0.512	0.536
Profile and Statistical	**0.543**	0.522	0.516	0.521	0.513
Emotional and Statistical	0.522	0.528	0.526	0.528	0.525
Profile, Emotional, and Statistical	0.523	0.530	0.535	0.532	0.540

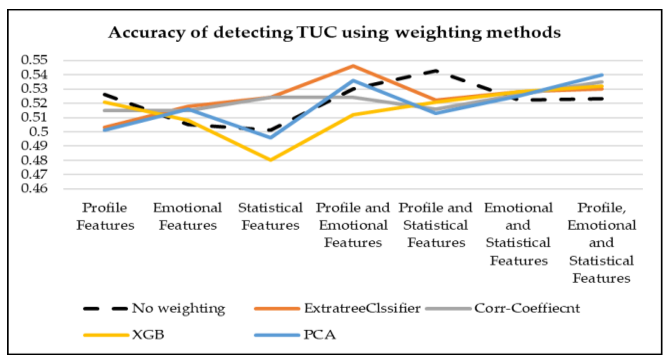

Fig. 4. Features weighting

C. Hybrid Method of Features Weighting and Selection

The proposal in this research assumes that by selecting and weighing features, we can achieve more accurate user-credibility detection results using SML methods. In this stage of our experiment, we executed a hybrid feature engineering technique by combining the most effective and interpretable methods to assess their influence on the accuracy of TUCD.

1) Selection method: For selecting we used SelectKBest which provides us with a list of the most effective features for detecting TUC, as well as using this method gives us the power to define the number of selected features as we determine the K value, our decision to use this method over the other one based on the observation that this method provides an improvement in the TUCD accuracy for all of the seven sub-datasets in our experiments, as well as it is based on statistical tests that have been used to select those features that have the strongest relationship with the output variable (target class) regardless of the internal correlations with other features.

2) Weighting method: On the other hand, our experiments proved that using tree-based models to weigh the features provides the best results for improving the detection of TUC; therefore, we used ExtraTreeClassifer to weigh the features in our datasets.

3) Hybrid method results: The results in Table IV and Fig. 5 show that the impact of this hybrid method on the accuracy of TUCD improved only two out of seven of our datasets, and the results in Table IV and Fig. 5 show that using the hybrid model improved only two groups out of seven groups that represented our datasets, but less than the improvement that was achieved by using the selection method alone, while the selection method proved that it improved the performance of all groups in the detection of TUC.

TABLE IV. THE HYBRID METHOD

Dataset Category	Raw Features	Selected Features	Weighted Features	Hybrid Method
		Select K-Best	*ExtraTree-Classifier*	*Select K-Best & ExtraTree-Classifier*
Profile	0.526	0.622	0.503	0.501
Emotional	0.505	0.603	0.518	0.522
Statistical	0.501	0.603	0.524	0.496
Profile and Emotional	0.530	0.620	0.546	0.503
Profile and Statistical	0.543	0.630	0.522	0.514
Emotional and Statistical	0.522	0.616	0.528	0.524
Profile, Emotional, and Statistical	0.523	**0.671**	0.530	0.501

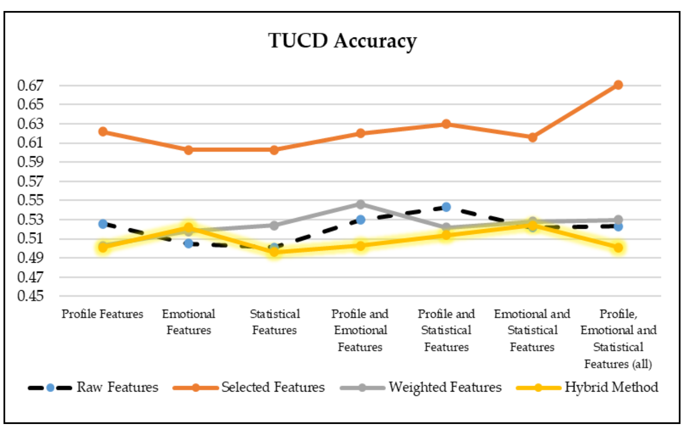

Fig. 5. The hybrid method

VI. DISCUSSION

In this section, we extensively discuss the research findings on feature engineering for TUCD. Our investigation delves into the effects of various feature engineering methods, including feature selection, feature weighting, and the proposed hybrid model, on the accuracy of TUCD. As previously mentioned, our experiments were conducted using the ArPFN dataset [45], which encompasses profile, emotional, and statistical features.

A. Feature Selection

The findings of this research and our previous research [9] highlighted the impact of using selection methods on TUCD accuracy as follows:

1) Effectiveness of the method: Our observations point to the effectiveness of feature selection methods, including SelectKBest and correlation-based algorithms, in enhancing the accuracy of TUCD. This indicates that refining the feature space's dimensionality by removing redundant and irrelevant features can contribute to the development of more accurate models. Notably, the use of correlation-based algorithms proved more effective than the SelectKBest algorithm, consistently yielding higher accuracy in all sub-datasets utilized in this research.

2) Impact of feature categories: Although the accuracy of TUCD improved across all feature category datasets with the implementation of feature selection methods, it is evident that the impact of these methods varies across these feature categories. The most notable improvement, as depicted in Table II and Fig. 3, was observed in the dataset combining all profile, emotional, and statistical feature categories. In contrast, both the statistical features and emotional features datasets showed relatively less enhancement among other feature categories. This discrepancy emphasizes the importance of customizing feature-engineering techniques to suit specific feature types.

B. Feature Weighting

Feature weighting affected the accuracy of TUCD as seen in this research, and our previous research [10] as follows:

1) Effectiveness of the method: Feature weighting techniques, encompassing logistic regression coefficients, tree-based models, and PCA, played a crucial role in assigning weights or importance scores to the features in this study. These assigned weights were then used by the model to generate new weighted sub-datasets for training, allowing us to measure their impact on TUCD accuracy. The application of these methods, especially tree-based algorithms, positively influenced the detection accuracy in this model. Our findings, as illustrated in Table III and Fig. 4, indicate that five out of the seven sub-datasets exhibited improved performance when employing a tree-based algorithm, either ExtraTreesClassifier or XGB-Classifier. One dataset achieved comparable accuracy with the tree-based algorithm as with the Corr-Coefficient method, whereas another sub-dataset among the seven experienced improved accuracy using the Principal Component Analysis

(PCA) method. In contrast, two out of the seven sub-datasets demonstrated a decrease in performance upon the application of any of the four weighted methods

2) Impact of feature categories: The influence of feature weighting exhibits variations among distinct feature categories. Notably, profile and emotional features had maximum improvements in accuracy, particularly when using tree-based models for feature weighting. In contrast, the profile feature category and the combination of profile and statistical feature categories had a detrimental effect on TUCD accuracy when utilizing weighting techniques.

C. Hybrid Method

1) Effectiveness of the method: Referring to Table IV and Fig. 5, using the hybrid method by integrating feature selection using the SelectKBest method and the feature weighting method using the ExtraTreeClassifier algorithm did not improve the TUCD in our model.

2) Impact of feature categories: Compared with other feature engineering methods or even using raw data, the TUCD accuracy of the hybrid method was the worst for most datasets. This method did not outperform the feature selection method for all datasets but outperformed the feature weighting for only one dataset, which is the emotional feature dataset. It also increased the accuracy above the raw data in the two datasets, which were emotional features and a combination of emotional and statistical features.

VII. CONCLUSIONS

The results outlined in this study hold significant implications for the fields of SML, feature selection, and social media analysis. Our investigation of feature engineering techniques, mainly the selection, weighting algorithms, and the suggested hybrid model combined with various feature types offers valuable insights into how they impact the accuracy of detecting user credibility on Twitter. In our previous research [9] [10], we investigated various feature selection and weighting techniques. This study extends our research by investigating a hybrid method that combines both approaches. Our aim was to identify the best feature engineering methods for enhancing the TUCD. This was accomplished by comparing the accuracy of the results obtained from the feature selection, feature weighting, or their combination in a hybrid model. The conclusion drawn was that feature selection is the most effective approach for improving result accuracy, followed by feature weighting coming in second place. Unexpectedly, the use of the hybrid model had a negative impact on most of our experiments. Furthermore, the recognition of key features and understanding their influence on credibility detection offer valuable insights for refining current theories in digital communication. From a managerial perspective, our research offers practical guidance for combatting misinformation and enhancing credibility detection systems, assisting organizations in deploying tailored strategies for content moderation and user engagement. Beyond merely shaping theoretical frameworks, the methodological contributions of this study exert a palpable influence on managerial practices, paving the way for continuous exploration of the ever-changing landscape of user credibility within digital platforms. Such contributions significantly enrich the ongoing academic discourse in this field.

VIII. FUTURE WORK

While our research contributes valuable insights into feature engineering for TUCD, it is essential to acknowledge certain limitations. Firstly, our experiments relied on the ArPFN dataset [45], which, while comprehensive, might not encapsulate all facets of Twitter user behavior. To address this, future studies should explore diverse datasets to validate our findings and ensure the generalizability of feature engineering methods. Additionally, our research focused on a subset of feature engineering techniques, and the exploration of other methods, such as feature creation or embedding techniques, could offer further enhancements in TUCD accuracy. Ethical considerations, particularly biases and fairness in TUCD applied to social media data, necessitate future research to address these concerns. Furthermore, our research primarily conducted batch analysis on historical data, highlighting the need for exploration into real-time or streaming TUCD methodologies. Lastly, the concentration on Twitter data prompts future inquiries into the generalizability of feature engineering techniques across various social media platforms. Addressing these limitations will contribute to a more comprehensive understanding and robust application of TUCD in diverse contexts.

SUPPLEMENTARY MATERIALS

The following supporting information can be downloaded at: www.mdpi.com/xxx/s1, Figure S1: title; Table S1: title; Video S1: title.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Gitlab at https://gitlab.com/bigirqu/ArPFN, reference number [45], (accessed on 5 January 2023).

CONFLICTS OF INTEREST

The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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