Cost-Sensitive Boosting Pruning Trees for Depression Detection on Twitter

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Abstract—Depression is one of the most common mental health disorders, and a large number of depressed people commit suicide each year. Potential depression sufferers usually do not consult psychological doctors because they feel ashamed or are unaware of any depression, which may result in severe delay of diagnosis and treatment. In the meantime, evidence shows that social media data provides valuable clues about physical and mental health conditions. In this paper, we argue that it is feasible to identify depression at an early stage by mining online social behaviours. Our approach, which is innovative to the practice of depression detection, does not rely on the extraction of numerous or complicated features to achieve accurate depression detection. Instead, we propose a novel classifier, namely, Cost-sensitive Boosting Pruning Trees (CBPT), which demonstrates a strong classification ability on two publicly accessible Twitter depression detection datasets. To comprehensively evaluate the classification capability of CBPT, we use additional three datasets from the UCI machine learning repository and CBPT obtains appealing classification results against several state of the arts boosting algorithms. Finally, we comprehensively explore the influence factors for the model prediction, and the results manifest that our proposed framework is promising for identifying Twitter users with depression.

Index Terms—Data mining, boosting ensemble learning, online depression detection, online behaviours

1 INTRODUCTION

Depression is one of the most common mental illnesses. It is estimated that nearly 360 million people suffer from depression [1]. In Britain, 7.8% of people meet the criteria of depression diagnosis, and 4-8% will experience depression in their lifetime [2]. Andrade et al. [3] reported that the probability for an individual to encounter a major episode of depression within a period of one year is 3-5% for males and 8-10% for females. Because of depression, about one million people of those committed suicide annually in the world [1].

Depressed people may have a variety of symptoms: having troubles in going to sleep or sleeping too much, lacking of passion or feeling disappointed [4]. In clinical exercises, psychological specialists are looking for reliable methods to detect and prevent depression. Yang et al. [5] investigated the relation between vocal prosody and changes in depression severity over time. Alghowinem et al. [6] examined human behaviours such as speaking behaviours and eye activities associated with major depression. Diagnostic and Statistical Manual of Mental Disorders [7] is an important reference for psychological doctors to diagnose depression. There are nine classes of depression symptoms recorded in the menu, describing the distinguishing behaviours in our daily life. Nevertheless, the symptoms of depression disorders evolve over time and it has been advised to dynamically update the criteria of depression diagnosis [1].

On the other hand, depression sufferers who do not receive timely psychotherapy will develop worse conditions. More than 70% of people in the early stage of depression do not consult psychological doctors, and their conditions deteriorated [7]. González-Ibáñez et al. [8] reported that people are somehow ashamed or unaware of depression which makes them miss timely treatment. Choudhury et al. [9] and Neuman et al. [10] proposed to explore the correlation of depression sufferers with their online behaviours on social networks.

With the explosive growth of computer network applications, social networks have become an indispensable part of many people’s daily lives. 62% of the American adults (age 18 and older) use Facebook, whilst the majority of the users (70%) visit Internet daily and a large portion of the users access to Internet multiple times each day [11]. There are 1.10 billion posts on Facebook every day. Twitter and Tumblr also have 500 and 77.5 million users who are active per day, where 70% of the Twitter users log in every day [11]. Therefore, social networks provide a means for capturing behavioural attributes

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that are relevant to an individual’s thinking, mood, communication, activities and socialisation [9]. Research studies reveal that collecting social networking information for analysing human physical and mental wellness is possible [12], [13]. Neuman et al. [10] developed working methods for recognising associated signals in the user’s posts on social networks, which suggest whether or not clinical diagnosis is required, based on his/her naturally occurring linguistic behaviours. Salawu et al. [14] detected cyber-bullying on social networks by comparing textual data against the identified traits. Nguyen et al. [15] utilised psycholinguistic clues to conduct sentiment analysis on users’ posts to detect depressed users online. Hence, it is feasible to detect depression via social networks.

Our proposed framework is shown in Fig. 1. In the first phase, we conduct data preprocessing and extract discriminative features from the posts of Twitter users, while the second phase presents a new Cost-sensitive Boosting Pruning Trees method based on the Discrete Adaboost [16] to classify the users. Our new contributions reported in this paper are:

1) We propose a novel resampling weighted pruning algorithm which dynamically determines optimal depths/layers and leaves of a tree model. The pruning procedure can support the boosting training and improve the robustness of the base tree estimator.

2) We combine the proposed pruning process with a novel cost-sensitive boosting structure within an ensemble framework, namely Cost-sensitive Boosting Pruning Trees (CBPT). By introducing cost items into the learning procedure of the boosting paradigm, we highlight the uneven identification importance among the samples so that the boosting paradigm intentionally biases the learning towards the samples associated with higher identification importance.

3) We conduct comprehensive experiments to justify the significance of our proposed framework against two Twitter depression detection datasets, i.e., Tsinghua Twitter Depression Dataset (TTDD) and CLPsych 2015 Twitter Dataset (CLPsych2015). The experimental results demonstrate that the prediction results are explainable against the ground-truth and our proposed framework can effectively identify Twitter users with depression.

2 RELATED WORK

In the literature, questionnaire or online interview is one of the common means used in depression diagnosis. Lee et al. [17] investigated whether or not interviewees have depressive trends using a choice questionnaire. Park et al. [18] conducted a face-to-face interview with 13 active Twitter users to explore their depressive behaviours. These questionnaires and interviews have several limitations. For example, they are time-consuming and hard to be generalised. On the other hand, because of the explosive growth in the popularity of social networks, online depression detection has attracted large interests in recent years.

Many research studies for online depression detection have focused on feature detection. Choudhury et al. [9] introduced measures (e.g., egocentric social graphs and description of anti-depressant medications) to quantify the online behaviors of an individual for a year before s/he reports the onset of depression. Park et al. [19] explored the use of languages in describing depressive moods using real-time moods captured from Twitter users. Saha et al. [20] analysed the content information of depressed users’ posts by extracting topical features. Most recently, Shen et al. [7] extracted six groups’ features such as user profile and engagement with online application programming interface (API) to interpret the online behaviours of depression users. However, most previous research studies focus on exploring new features of depression behaviours whilst ignoring the fitness of the classification models.

Shen et al. [7] presented a multi-modal depressive dictionary learning model (MDDL) which combines sparse dictionary learning with logistic regression to identify depressed users. Nadeem et al. [21] conducted experiments to classify Major Depression Disorder (MDD) using four binary classifiers, e.g., decision tree and naive bayes. Also, Choudhury et al. [9] and Shuai et al. [22] proposed a depression detection framework based on support vector machine. Nevertheless, these established classifiers cannot achieve consistent performance due to noise or errors in the data.
In recent years, deep learning based methods for online depression detection attracted the attention of researchers. For example, Shen et al. [23] proposed a cross-domain depression detection framework which transfers the knowledge of Twitter to classify the instances of Weibo. Their proposed method aims to improve the recognition performance in the poorly labeled target domain (Weibo) utilising the rich data of the source domain (Twitter). Ray et al. [24] proposed a multi-level attention network that combines the text, audio and video features to classify depressed people. Gamaarachchige et al. [25] proposed a multi-task, multi-channel and multi-input framework that fuses multiple input features (e.g., emotion labels, tokens) and learns knowledge from multiple classification tasks. Their proposed method achieved good performance in the CLPsych 2015 dataset [26]. Orabi et al. [27] proposed a word embedding optimisation method which combines multiple word embedding features (e.g., Skip-gram, CBOW). They used this technique to extract text features from the Twitter users’ posts and identified the depressed users. These deep learning based method can achieve promising performance on depression detection especially on multi-level feature fusion and knowledge transfer. However, these methods lack clear interpretations to the model predictions as of which specific factor influences the predicted depression risk.

Decision trees based ensemble learning brings up the possibility of developing a powerful and interpretable model. Decision trees can reveal the feature effects to the prediction and ensemble learning uses multiple learning algorithms to obtain better predictive performance than that of using any of the constituent learning algorithms alone [28], [29], [30], [31]. Our framework is based on Adaboost which is one of the typical ensemble meta-algorithms to reduce biases and variances in supervised learning [32]. In general, Adaboost employs decision dump as its base estimator. However, decision dump cannot fit well the training data because of its simple structure. Adaboost with decision dump does not perform well in complex datasets [30]. Boonyanunta et al. [33] proposed a method to improve Adaboost’s performance by averaging the estimators’ weights or reordering estimators. Based on Adaboost, Friedman et al. [34] reported Gradient Boost Decision Trees (GBDT) which is the generalisation of boosting to arbitrary differentiable loss functions. Unfortunately, GBDT can be over-fitting if the data is noisy and the training process of GBDT is time consuming. Chen et al. [35] introduced an advanced Gradient Boost algorithm (called ‘XGboost’) based on GBDT in 2016. Although XGBoost is more flexible and efficient than GBDT, it has many parameters that are hard to tune.

In this paper, we propose a novel classification algorithm based on AdaBoost that can mitigate the influence of noise or errors and have a strong fitness and generalisation ability. We introduce the details of the proposed algorithm in Section 4. In addition, we summarise the discussed classification methods in Table S4, Supplementary A, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TAFFC.2022.3145634.

3 DATA PREPROCESSING AND FEATURE EXTRACTION

In this paper, we intend to analyse depression users’ online behaviours. As the scripts on social networks may be random and unpredictable, features with different noise may be obtained and influence the detection accuracy. Before feature extraction is implemented, we carry out the following preprocessing procedure: (1) Minimisation of the influence of noisy samples. Inspired by the work of Yazdavar et al. [36], we remove the noisy samples from the dataset where the posting number of the samples is less than five. These samples cannot provide sufficient information for analysing the users’ behaviours or topic modelling. (2) Processing of irregular words. The words on social networks may look irregular because of mistaken spelling or abbreviations. We use the Textblob API reported in [37] (commonly used in natural language processing tasks) to remedy the wrong type of words. (3) Stemming. We expect to perform statistical analysis on commonly used words of control and depressed users separately and conduct topic modelling on the users’ posts. Words must be of unified representations regardless of tense and voice. Hence, we utilise the SnowballStemmer algorithm reported in [38] to deal with these words. For instance, “accepting” and “accepted” can be converted to “accept”. Afterwards, we extract three feature categories as follows and the proposed framework is shown in Phase 1 of Fig. 1.

(1) User’s Profile Features: The user’s profile features contain the user’s individual information on social networks. We collect 4 different features here: total_favourites reflects the number of posts that this particular user favours during his/her account’s lifetime; listed_count shows the number of the public list that this user holds a membership within. We collect the number of the user’s friends and followers which well characterise the author’s egocentric social networks.

(2) Social Interaction Features: Park et al. [19] discovered that depressed users are less active in social networks, and depressed users regard social networking as a tool for social awareness and emotional interaction. Thus, we extract retweet count, mention count (e.g., @someone) and favourites count (indicating how many times this post has been favoured by the other users) to describe the behaviours of the user interacting with others. Besides, we collect the posting number and time distribution to demonstrate the user’s activeness on social networks.

(3) Linguistic Features: The content of the posts on social networks can intuitively reflect a person’s mood and attitude. Depressed users may post more negative words than control users [7], [9], [19], [39]. Hence, we count the numbers of negative and positive words in the tweets using the NLTK toolkit [40]. In addition, we collect the numbers of emoji and emotions from the texts to form relevant features. In order to comprehensively explore the semantics, Resnik et al. [41] examined the difference of the concerned topics between depressed and control users by topic modeling and observed that topic modeling might be effective for depression detection. In our work, we utilise the Latent Dirichlet Allocation (LDA) approach presented in [42] to extract topic distributions from the tweets.

Finally, the extracted feature sets are used to train our proposed classifier CBPT, which is shown in Phase 2 of Fig. 1 and we provide the details of the extracted feature dimensionality in Table S1, Supplementary A, available online.
4 PROPOSED METHOD

4.1 Discrete Adaboost

Our classification algorithm is built upon the discrete Adaboost algorithm proposed by Freud et al. [16]. Algorithm 1 presents the baseline scheme of the discrete Adaboost that combines many simple hypotheses (called weak learners) to form a strong classifier for the task [30]. The algorithm can be summarised as follows: (1) Training multiple base classifiers sequentially and assigning a weight value \( \ln(\beta_m) \) according to its training error \( \varepsilon_m \). (2) The samples misclassified by the preceding classifier are assigned a higher weight \( w_{m+1,i} \), which will let the classifier pay more attention to these samples. (3) Finally, combining all the weak classifiers with their weights to obtain an ensemble classifier \( G(X) \). As we have discussed above, Adaboost may not perform well on a complex dataset, and hence we propose the CBPT algorithm to improve the performance of Adaboost in two aspects: (1) We improve the fitting and generalisation ability of the base classifier. (2) We propose a novel boosting structure to strengthen the sample re-weighting process.

Algorithm 1. Discrete Adaboost Algorithm

Input: A training set \( D = \{(X_i, y_i)\}_{i=1}^N \). Output: A model \( M_k(X) \) which is based on \( K \) decision trees with their corresponding weight.

1: procedure ADABOOST(D)
2: Initialise sample weight distribution \( \frac{1}{N} \).
3: for \( k \in (1, K) \) do
4: Fit an estimator \( M_k(X) \) to the training data with \( W_k \).
5: Let \( w_i = 1 \) if the \( i \)th case is classified incorrectly, otherwise zero.
6: Compute training error \( \varepsilon_k = \sum_{i=1}^N w_k(i) u_i \).
7: Update sample’s weight \( w_k(i) = \frac{w_k(i) \beta_k}{\sum_i w_k(i) \beta_k} \), where \( \beta_k = \frac{1}{\varepsilon_k} \).
8: \( M_k(X) \leftarrow M_{k-1}(X) + \log(\varepsilon_k) M_k(X) \).
9: end for
10: return \( M_k(X) \)
11: end procedure

4.2 Cost-Sensitive Boosting Pruning Trees

In this section, we propose an ensemble method that combines an improved Adaboost algorithm with pruned decision trees for classification. Here, we still employ a decision tree as the base estimator because of its flexibility and interpretability. Decision dump often suffer from under-fitting whilst a full tree has a high variance. We here consider pruning trees in order to increase system generalisation. In our algorithm, we first apply all the training samples and allow a decision tree to fully grow, and then use the cost-complexity pruning method reported in [43] to prune certain branches of the trees and use the modified criterion to evaluate the system performance with the pruned trees and update the weights. Afterwards, the above steps will be executed iteratively till the maximum number of the trees is reached. To formulate our algorithm, we here declare the used notations in advance. In particular, we denote the training dataset as \( D = \{(X_i, y_i)\}_{i=1}^N \) and \( X^{(i)} \in \mathbb{R}^{N \times V} \) is the sample feature vector where \( N \) represents the set size and \( V \) is the feature dimension. \( y_i \) represents the training target. We employ \( W = \{(w_k(i)) \in \mathbb{R}^N \}_{i=1}^{K} \) to represent the set of the sample weight distribution. \( K \) is the number of the estimators (iterations) and each sample’s weight is initialised to \( \frac{1}{N} \) in the first iteration during the normalisation. Furthermore, we use \( \theta_k \) and \( M_k(X) \) to denote the \( k \)th estimator’s weight and the ensemble classifier.

4.2.1 Resampling Weighted Pruning Algorithm

In most of the previous boosting algorithms [34], [35], [44], except num trees, max depth and num leaves are two key hyperparameters which affect the classifier’s performance significantly. Manually tuning the hyperparameter combinations is a heavy task and it is hard to find the best parameter combinations for different datasets. Therefore, we propose a novel technique called resampling weighted pruning to automatically prune redundant leaves and produce robust tree models, where weights are used to establish a relationship between the pruning and boosting practice.

First, we denote the original learning sample set \( D \) which is divided randomly into \( S \) subsets, \( \{D_s\}_{s=1}^S \) and the training set of each subset is \( D^{(s)} = D - D_s \). The tree \( T_{\text{max}} \) comes from the original set \( D \) and we build a complete tree on each subset \( D^{(s)} \). We present the cost function of the decision trees as follows:

\[
\mathcal{L}(T; w_k) = \sum_{T^i} 1 - \frac{C}{\sum w_k(i)} \left( \sum_{i=1}^C \frac{w_k(i)}{\sum w_k(i)} \right)^2 \tag{1}
\]

where \( |T^i| \) is the leaves’ number, \( C \) denotes the class number and the sample of class \( c \) is defined as \( i_c \). The loss of the decision trees is the sum of all the leaf nodes’ gini impurity [45]. A complete tree’s loss \( \mathcal{L}(T_{\text{max}}; w_k) \) is zero because each leaf node only includes a single class’s samples. But \( \mathcal{L}(T; w_k) \) will increase in the pruning process where the pruned nodes are merged with their parents’ nodes. Therefore, the present cost function is not a good measure of selecting a subtree because it always favours large trees. Thus, the penalty term, regularization parameter \( \alpha \) and the tree leaves \( |T^i| \) are added to the cost function. The new cost function is defined as follows:

\[
\mathcal{L}_{\alpha}(T; w_k) = \mathcal{L}(T; w_k) + \alpha |T^i| \tag{2}
\]

The penalty term favours a simple tree when \( \alpha \) is constant and \( |T^i| \) decreases with pruning.

Now, the variation in the cost function is given by \( \mathcal{L}_{\alpha}(T - T_i; w_k) - \mathcal{L}_{\alpha}(T; w_k) \), where \( T_i \) represents a branch with the node at \( t \) and a tree pruned at node \( t \) would be \( T - T_i \). Next, the cost of the pruning on the internal nodes is calculated by equating \( \mathcal{L}_{\alpha}(T - T_i; w_k) \) to that of the branch at node \( t \)

\[
\mathcal{L}_{\alpha}(T - T_i; w_k) - \mathcal{L}_{\alpha}(T; w_k) \leq 0 \Rightarrow \mathcal{L}(T; w_k) - \mathcal{L}(T_i; w_k) \leq 0 \Rightarrow \mathcal{L}(T; w_k) + \alpha - \mathcal{L}(T_i; w_k) - \alpha |T^i| \leq 0 \Rightarrow \mathcal{L}(T; w_k) - \mathcal{L}(T_i; w_k) - \alpha |T^i| \leq 0 \leq \alpha |T^i| - 1 \tag{3}
\]
We define

\[ g(t) = \frac{\mathcal{L}(t; w_k) - \mathcal{L}(T_i; w_k)}{|T_i| - 1} \quad (4) \]

We will prune branch \( T_i \) with the decrease of the cost function value when \( \alpha \geq g(t) \). The order of pruning is performed by setting \( \alpha = \arg \min_t g(t) \) in order to find the suitable branch, which should be pruned, and the process will be repeated until the tree is left with the root node only. This provides a sequence of subtrees \( \{(T^{(s)}_i)\}_{j=1}^J \) with the associated cost-complexity parameters \( \{(\alpha_j); \forall \alpha \in \mathbb{R}\}_{j=1}^J \) where \( J \) is the length of the subtree sequence.

For \( \alpha \), we apply the pruned tree \( T^{(s)}_j \) to predicting the estimations in the \( s \)th test set, resulting in the following error rate

\[ \mathcal{E}^{(s)}_j = \frac{1}{S} \sum_{s=1}^{S} \mathcal{E}^{(s)}_a \quad (5) \]

where \( \mathcal{E}^{(s)}_a \) denotes the index of the misclassified sample's weight, \( w^{(i)}_k \) is the sample's weight of the test set \( D_s \) and \( \mathcal{E}^{(s)}_a \) represents the misclassified rate of set \( D_s \). Hence, the average misclassified rate of \( S \) is

\[ \mathcal{E}_j = \frac{1}{S} \sum_{s=1}^{S} \mathcal{E}^{(s)}_j \quad (6) \]

and we define

\[ \alpha^* = \arg \min_{\alpha} \mathcal{E}_j, \quad \exists \alpha_j > 0 \quad (7) \]

which is the best pruned tree obtained by pruning \( T_{\text{max}} \) till \( \mathcal{L}_D(T_{\text{max}}; w_k) \) reaches the minimum. The pseudocode of our resampling weighted pruning algorithm is shown in Algorithm 2.

**Algorithm 2. Resampling Weighted Pruning Algorithm**

**Input:** A training set \( D \) with corresponding weight \( W_k \).

**Output:** A pruned tree estimator \( M_k(X) \).

1: \hspace{1cm} function BestPrunedTree (\( D, W_k \))
2: \hspace{1cm} Randomly split the learning samples \( D \) into \( S \) folds, \( \{D_i\}_{i=1}^S \).
3: \hspace{1cm} Grow a decision tree \( T_{\text{max}} \) on the whole set \( D \).
4: \hspace{1cm} for \( s \in [1, S] \) do
5: \hspace{2cm} Fit a decision tree \( T^{(s)}_i \) to subset \( D^{(s)} \).
6: \hspace{2cm} Generate subtree sequence \( \{(T^{(s)}_a); \forall \alpha \in \mathbb{R}\}_{j=1}^J \) by Eq. (3).
7: \hspace{2cm} Generate subtree sequence \( \{(T^{(s)}_j)\}_{j=1}^J \) \hspace{1cm} \{ \begin{align*}
1. \text{Calculate } g(t) \text{ using Eqs. (3) and (4)}. \\
2. \text{Set } \alpha = \arg \min g(t) \text{ and prune the branch } T_i. \\
3. \text{Recursively repeat till the tree only has root nodes.}
\end{align*} \}
8: \hspace{1cm} Calculate \( \mathcal{E}^{(s)}_j \) \hspace{1cm} \text{Eq. (5)}.
9: \hspace{1cm} end for
10: \hspace{1cm} Compute average error rate \( \mathcal{E}_j \) against each subtree.
11: \hspace{1cm} \alpha^* = \arg \min_{\alpha} \mathcal{E}_j, \quad \exists \alpha_j > 0.
12: \hspace{1cm} The best pruned tree estimator \( M_k(X) \) \hspace{1cm} Prune \( T_{\text{max}} \) till \( \mathcal{L}_D(T_{\text{max}}; w_k) \) becomes minimal.
13: \hspace{1cm} return \( M_k(X) \).
14: end Function

**4.2.2 Tree-Based Cost-Sensitive Boosting Structure**

As shown at steps 7 and 8 of Algorithm 1, Adaboost employs the training error \( \epsilon_m \) as the evaluation criterion of the base estimator’s performance, to set up the estimator’s weights and update the samples’ weights. All the misclassified samples receive the same weights in each iteration. In general, we assume that misclassified samples should be given different weights according to the “hardness” of the samples - harder samples are of more weights. We now propose a novel boosting architecture namely Tree-based Cost-sensitive Boosting which utilizes the tree model to assess the “hardness” of the training samples and optimize the boosting process.

In the first step, we apply a complete decision tree to the training data \( D \) and prune it in order to obtain the best tree estimator \( M_k(X) \). A complex tree model has more depths. Similarly, the deeper the landing node of a sample is, the harder the sample can be classified. Here, we present a new and effective depth penalty term as follows:

\[ DP^{(i)}_k = \frac{\Psi_d(\sigma^{(i)}_k - \min(\sigma^{(i)}_k))}{\max(\sigma^{(i)}_k) - \min(\sigma^{(i)}_k)} + \eta_d; \quad \Psi_d \in \mathbb{N}^+, \eta_d \geq 1 \quad (8) \]

where \( \sigma^{(i)}_k \) represents the landing node depth of sample \( i \), \( \max(\sigma^{(i)}_k) \) and \( \min(\sigma^{(i)}_k) \) are the maximum and minimum values in the node depth array \( \sigma^{(i)}_k \), \( \psi_d \) and \( \eta_d \) are two hyper-parameters where \( \psi_d \) is the percentage of data scaling, and \( \eta_d \) is the lower limit of the penalty term. The depth penalty term is a coefficient that is multiplied with the original sample’s weight to enable hard samples to gain more weights in the next iteration.

The landing node’s depth can be regarded as the global evaluation of the “hardness” of a sample associated with the tree structure. In the pruning procedure, the pruned samples are included in the parent node of the pruned branch. Here, we use node impurity to represent the local evaluation of the “hardness” of a sample. For instance, when two samples land in different leaf nodes but with the same depth, the sample of low node impurity will be given more weights as the sample is separated from the most samples of the same class in the feature space. Hence, the impurity penalty term \( DP^{(i)}_k \) is defined as follows:

\[ DP^{(i)}_k = \frac{N - N^{(i)}_k}{2N} - \frac{E^{(i)}_{\text{po}x}[\log q(x)]\mu^{(i)}_k - N}{N} \quad (9) \]

\[ DP^{(i)}_k = \left( \left\| DP^{(i)}_k \right\|_{-\infty} - \left\| DP^{(i)}_k \right\|_{-\infty} \right) \frac{(\sigma^{(i)}_k - \min(\sigma^{(i)}_k))}{\max(\sigma^{(i)}_k) - \min(\sigma^{(i)}_k)} \quad (10) \]

Eq. (9) is an inverse transformation of the impurity value, where \( \mu^{(i)}_k \) is the sample number in the landing node, \( E^{(i)}_{\text{po}x}[\log q(x)] \) is the impurity value either Cross Entropy or Gini Impurity, \( p(x) \) and \( q(x) \) are the predicted probability distributions of the sample \( X_i \). Similarly, in Eq. (10), we employ the data scaling for \( \sigma^{(i)}_k \) and obtain the impurity penalty term \( DP^{(i)}_k \), \( \left\| DP^{(i)}_k \right\|_{-\infty} \) and \( \left\| DP^{(i)}_k \right\|_{-\infty} \) are positive and negative infinity norms of the depth penalty vector which are used to limit the range of data scaling.
The proposed two penalty terms mainly rely on the landing positions of the samples in the pruned tree structure. Algorithm 3 returns the learning sample position by recursively following the sample’s decision path as follows:

\begin{algorithm}[h]
\caption{Recursively Find Landing Node}
\begin{algorithmic}[1]
\Function{TreeRecursion}{l}{X_i, y_i}\Comment Find the tree node where the sample land
\If {Node(l) \equiv Leaf}\Comment Check if node l is a leaf
\State \return \sigma_k^{(i)} \cdot \mu_k^{(i)}
\Else
\If {X_i^{(i)} < \text{Threshold}^{(i)}}\Comment Determine if the sample flow down to left or right child
\State \return \text{TreeRecursion}(a_l, X_i, y_i)
\Else
\State \return \text{TreeRecursion}(b_l, X_i, y_i)
\EndIf
\EndIf
\EndFunction
\end{algorithmic}
\end{algorithm}

In each iteration \( k \), the ensemble boosting aims to minimise an exponential loss function, described by

\[
\hat{L}(M) = \sum_{i=1}^{N} \exp[-y_i(M_{k-1}(X_i) + \theta_k M_k(X_i))] \quad (11)
\]

where \( M_{k-1}(X) \) represent the \( k - 1 \) trained pruned trees and \( w_k^{(i)} = \exp(-y_i M_{k-1}(X_i)) \), \( \theta_k \) is the estimator weight of the \( k \)th pruned tree. We can calculate the first order partial derivative of \( \hat{L}(M) \) with respect to the estimator weight \( \theta_k \)

\[
\frac{\partial \hat{L}(M)}{\partial \theta_k} = \sum_{i=1}^{N} \frac{\partial}{\partial \theta_k} w_k^{(i)} \exp(-y_i \theta_k M_k(X_i))
= \sum_{i:y_i \neq M_k(X_i)} w_k^{(i)} e^{\theta_k} + \sum_{i:y_i = M_k(X_i)} w_k^{(i)} e^{-\theta_k}
= \frac{\partial}{\partial \theta_k} \left( (1 - \varepsilon_k) e^{\theta_k} + \varepsilon_k e^{-\theta_k} \right)
= (\varepsilon_k - 1) e^{\theta_k} + \varepsilon_k e^{-\theta_k}
\]

By taking zero to the left hand side of Eq. (12), we have

\[
\theta_k \propto \frac{1}{2} \log \left( \frac{1 - \varepsilon_k}{\varepsilon_k} + \log (C - 1) \right) \quad (13)
\]

where \( \varepsilon_k \) is the training error of pruned tree \( M_k(X) \). \( \log (C - 1) \) is a regularisation term and \( C \) is the number of classes.

The two penalty terms are taken as the interference factors to influence the updating of the sample’s weights and the misclassified samples employ different weights according to their landing positions in the pruned tree structure. The iterative training of the cost-sensitive boosting will stop if it converges (i.e., \( \mu_k \) reaches zero) or we reach the maximum iteration number \( K \). The whole algorithm is illustrated in Algorithm 4, linked with the two proposed functions.

\begin{algorithm}[h]
\caption{Cost-Sensitive Boosting Pruning Trees Algorithm}
\begin{algorithmic}[1]
\Function{CostBoosting}{D, W} \Comment A training set \( D = \{(X_i, y_i)\}_{i=1}^{N} \) with sample distribution \( W = \{(w_k^{(i)}) \}_{i=1}^{N} \)
\State \begin{align*}
\text{Input:} & \quad \text{A training set } D = \{(X_i, y_i)\}_{i=1}^{N} \\
\text{Output:} & \quad \text{A Cost-sensitive Boosting Pruning Trees model } M_k(X)
\end{align*} \\
\end{algorithmic}
\end{algorithm}

5 Experimental Setup

To demonstrate the effectiveness of the proposed CBPT for Twitter depression detection, we conduct experiments on two publicly accessible datasets: the Tsinghua Twitter Depression Dataset (TTDD) and the CLPsych 2015 Twitter Dataset (CLPsych2015). All experimental procedures have been approved by the Ethical Review body of University of Leicester. In this section, we describe the setup details of our evaluation.

TTDD\(^1\): The Twitter database was collected by Shen et al. [7] in 2017 for depression detection. The Twitter database has three parts: (1) Depression Dataset D1: The dataset was created based on the tweets collected between 2009 and 2016, where the users were labelled as depression if their

\(1. \) http://depressiondetection.droppages.com/
anchor tweet satisfied the pattern “(I’m/1 was/1 am/I’ve been) diagnosed depression”. (2) Depression Dataset D2: This dataset contains Twitter messages where users were labelled as non-depressed if they had never posted any tweets containing the character string “depress”. (3) Depression Dataset D3: Shen et al. [7] constructed an unlabelled large dataset D3 for depression candidate. Based on the tweets shown in December 2016, this unlabelled depression candidate dataset was established where the user were recorded if their anchor tweet loosely contained the character string “depress”. There are 2558, 5304 and 58810 samples stored in D1, D2, D3, respectively. Each sample of these three datasets contains one-month post information of a Twitter user. In this paper, we employ the well labelled datasets D1 and D2 to evaluate our classification algorithm’s performance and analyse the online behaviours of depression users.

CLPsych 2015. The dataset was established by John Hopkins University for a depression detection task in 2015 [26]. The dataset contains public Twitter users’ posts between 2008 and 2013 via the Twitter application programming interface (API). Similarly, possible mental disease sufferers are labeled as depression or post-traumatic stress disorder (PTSD) according to their self statement of diagnosis, such as “I was just diagnosed with depression or PTSD...”. Furthermore, they conducted careful pre-processing and anonymisation operations, such as filtering the users whose tweets are fewer than 25 and removing individual information. Finally, they manually examined and refined the annotation of each collected Twitter user’s logs by using a semi-supervised method. The processed dataset consists of 477 depressed users, 396 PTSD (an anxiety disorder caused by very stressful, frightening or distressing events) users and 873 control users. For each user, up to their most recent 3000 public tweets were included in the dataset.

Implementation Details. We implement the proposed CBDT and other benchmark experiments using the Scikit-learn framework [46] and deploy all the experiments on a 8-core Intel Xeon skylake 2.6GHz CPU with 64GB RAM. The source code will be publicly accessible.

6 Experimental Results

In this section, we present both quantitative and qualitative experimental results of different trials. We first conduct an ablation study of our method to show the impact of the pruning procedure and the cost-sensitive boosting scheme on the classification performance. We also compare our proposed Twitter depression detection framework with several state-of-the-art methods using the aforementioned two Twitter datasets. Finally, we justify the specification factors for depression prediction by our model.

6.1 Ablation Studies

In order to evaluate our proposed CBPT comprehensively, besides the two Twitter datasets, we also use three publicly accessible datasets (e.g., LSVT, Statlog, Glass) from the UCI machine learning repository [47] to examine our method’s classification performance. We compare our method with Real Adaboost [48], XGBoost [35], LogitBoost [49], LightBoost [50] and KiGB [44], which are state-of-the-art Boosting methods. We also investigate the performance of the standard Discrete Adaboost and combine the Discrete Adaboost structure with the pruning procedure (Adaboost+PT) as a comparison method to validate the effectiveness of our newly added components. We summarise the datasets’ details in Table S5, Supplementary B, available online.

For the performance comparison, we use Accuracy and F1-score as evaluation metrics. The UCI datasets have supplied feature vectors and the ground truth, so we use the same feature extraction procedure (aforementioned in Section 3) to extract features vectors from the two Twitter datasets. We use 5-fold cross-evaluation on the five datasets, where the training size is 75% and the test size is 25%. To seek a fair comparison, we have evaluated different settings of the hyperparameters for the compared methods and the best results on the test set are recorded. Some key hyper-parameters include: (1) $\text{Num leaves} \in \{64, 128, 256\}$, which control the size of each tree. (2) $\text{Max depth} \in \{5, 10, 15\}$, which limit the maximum depth of each tree. (3) $\text{Learning rate} \in \{0.1, 0.5, 1\}$, which determine the weight coefficient of each tree. (4) We fix the $\text{tree number}$ in all the classifiers to 500 in order to obtain converging results. More details of the parameter setting are listed in Table S6-10, Supplementary B, available online.

The results of classification on the five datasets are presented in Table 1. We observe that CBPT obtains the best performance in the two Twitter datasets and achieves 92.21\% accuracy and a F1-score of 91.20\% in the Statlog dataset. But in the LSVT and Glass datasets, the ‘ablation’ method Adaboost+PT results surpass CBPT by 1\% and 2\% separately. The reason is that the cost-sensitive boosting structure may be weak in the small-scale datasets. The Adaboost+PT outperforms the baseline Discrete Adaboost in the five datasets, confirming the effectiveness of our proposed pruning procedure. In general, the classification performance of CBPT for the five datasets is better than the other boosting methods except Adaboost+PT. To find out why this occurs, we undertake the following experiments.

Figs. 2a, 2b, 2c, 2d and 2e show the testing errors per iteration of the boosting classifiers for the five datasets. We observe that CBPT uses fewer trees to produce a comparable testing error in the TTDD, CLPsych 2015, and Statlog datasets. Comparing Adaboost+PT with CBPT, we witness the cost-sensitive boosting structure is effective to speed up the convergence of the algorithm in the TTDD, CLPsych 2015, and Statlog datasets. In the LSVT and Glass datasets, the cost-sensitive boosting structure is not helpful to improve the testing accuracy. As the LSVT and Glass datasets only have 128 and 214 samples respectively, we examine that in the cost-sensitive boosting structure, the newly added two penalty terms accelerate the weight updating and increase the variance in the small-scale datasets. To validate our assumption, we look at Figs. 3a, 3b, 3c, 3d and 3e. The accuracy of CBPT and Adaboost+PT increase as more training samples are added. In spite of being trained with small data, CBPT and Adaboost+PT still outperform the
baseline Discrete Adaboost, which verifies the pruning procedure effectively improves the models’ generalization ability. From Figs. 3a, 3b and 3d, CBPT outperforms Adaboost +PT after having been trained with 32.5% or more training data. We summarise that in the case of sufficient training data, the proposed cost-sensitive boosting structure can improve the robustness of the model.

### 6.2 Comparison With the SOTA Depression Detection Frameworks

In the above discussion, we have verified our proposed classifier CBPT outperforms the other SOTA boosting algorithms in the two Twitter depression detection datasets. We employ the same feature extraction procedure to extract features from the two Twitter datasets. We obtain 38 dimensional feature vectors from the TTDD dataset and 40 dimensional vectors from the CLPsych 2015 dataset (i.e., age and gender information are available so we extract the extra two features from the CLP dataset). The two feature matrices are used to train CBPT.

Tables 2 and 3 show the comparison results of depression detection. From Table 2, it is obvious that our framework achieves the best performance and surpasses the SOTA method of Shen et al. [7] by 3.39% on accuracy and 1.69% on F1-score. In the CLPsych 2015 leader-board, the detection performance is evaluated against three separate classification tasks, i.e., Depression versus Control, Depression versus PTSD and PTSD versus Control. In Table 3, the CBPT results are competitive and better than the other methods in the PvC task. Another advantage of our framework is that the dimensionality of our extracted feature is far less than that of the other methods. For example, Resnik et al. [53] employed a complicated Supervised LDA model to extract document vectors and combine these with large vocabularies (feature dimensionality is about 500).

### Table 1

Classification Results: [Mean Accuracy/F1 Score ± Standard Deviation] by Eight Boosting Classifiers for Five Public Datasets

| Algorithm       | TTDD     | CLPsych 2015 | LSVT    | Statlog  | Glass   |
|-----------------|----------|--------------|---------|----------|---------|
| Discrete Adaboost | 86.48±0.93 | 84.88±1.02 | 64.76±2.02 | 61.28±2.48 | 80.15±4.39 | 75.45±6.71 | 77.17±8.62 | 71.15±1.08 | 58.07±8.84 | 48.92±7.45 |
| Real Adaboost    | 85.79±0.85 | 84.21±0.98 | 61.42±3.75 | 57.70±3.45 | 81.72±3.30 | 78.05±5.09 | 70.34±4.29 | 62.54±4.26 | 40.64±11.68 | 29.72±19.01 |
| XBoost          | 87.42±0.56 | 86.03±0.57 | 68.62±2.62 | 64.66±3.25 | 84.12±2.54 | 79.66±5.76 | 91.74±0.79 | 90.13±0.85 | 74.36±10.83 | 69.56±11.55 |
| LogitBoost      | 86.54±0.22 | 85.01±0.28 | 61.48±3.24 | 57.32±3.79 | 80.09±6.80 | 76.00±5.65 | 90.33±0.63 | 88.23±0.59 | 75.27±6.74 | 71.84±8.98 |
| LightGBM        | 87.69±0.72 | 86.49±0.67 | 68.62±1.66 | 64.46±2.30 | 85.75±3.87 | 79.90±10.72 | 92.46±0.62 | 90.90±0.59 | 76.67±8.87 | 72.67±10.42 |
| KGB             | 87.73±0.68 | 86.29±0.68 | 67.66±2.05 | 62.79±1.27 | 81.69±5.53 | 77.76±4.83 | 91.40±0.70 | 89.71±0.59 | 77.13±8.94 | 67.87±12.84 |
| Adaboost+PT (Ours) | 87.70±0.77 | 86.34±0.83 | 69.71±2.74 | 65.71±3.34 | 86.52±5.37 | 82.45±7.98 | 87.13±1.05 | 85.04±1.08 | 79.02±2.94 | 72.70±9.06 |
| CBPT (Ours)     | 88.39±0.60 | 86.90±0.62 | 70.69±1.84 | 66.54±2.42 | 85.72±4.03 | 81.26±6.24 | 92.21±0.31 | 91.20±0.38 | 77.63±8.58 | 70.66±9.55 |

The Best results are shown in bold.

### Table 2

Detection Performance Compared With the SOTA Frameworks for the TTDD Dataset

| Method          | Accuracy | F1-score |
|-----------------|----------|----------|
| Shen et al. [7]  | 85%      | 85%      |
| Pedregosa et al. [46] | 73%      | 71%      |
| Song et al. [51] | 82%      | 81%      |
| Rolet et al. [52] | 76%      | 76%      |
| CBPT (Ours)     | 88.39%   | 86.90%   |

The Best results are shown in bold.
et al. [54] applied the unigram word features of 41687 dimensions to training their model. Our method only uses few features and achieves competitive performance for the CLPsych 2015 dataset. From the two comparison experiments, we can verify our proposed depression detection framework has satisfactory robustness on different datasets.

### 6.3 Explainable Depression Detection

Previous research studies [7], [21], [56] have widely analysed online behaviours of depressed users through examining features’ distributions or mean values and variances. But they have not explored which specific factors contribute to depression detection. Tree Shapley Additive Explanation (TreeSHAP) [57] is a game approach to explain the output of decision trees based models. The goal of TreeSHAP is to explain the prediction of any instance by measuring the contribution of each feature to the prediction. TreeSHAP treats Shapley Values [58] as the features’ contributions and uses all the advantages of Shapley Values: (1) TreeSHAP has a solid theoretical foundation in the game theory. (2) The prediction is fairly distributed over the features’ values. (3) TreeSHAP gives contrastive explanations that compares the prediction with the model’s expectation[28]. Hence, we integrate our framework with TreeSHAP to comprehensively investigate the influencing factors for the prediction results. We use the subset CvD of the CLPsych 2015 and the TTDD dataset for evaluating the depression risk factors, and other results (e.g., DvP, PvC subsets) are shown in Supplementary C, available online. Besides, we list the related formulas of TreeSHAP in Section A, Supplementary D, available online and we give an example for the calculation of the Shapley Values via decision trees in Section B, Supplementary C, available online.

In Section A, Supplementary D, available online, we describe that $\phi_{X_i}(f)$ represents the contribution of feature $X_i$ to the classifier’s prediction for instance $X$. In our depression detection datasets, we aim to explore the influencing factors for the predicted depression risk of Twitter users, so the value of $\phi_{X_i}(f)$ represents how much the predicted depression probability for instance $X$ has been affected by feature $X_i$.

Fig. 4 shows two confusion matrices of the prediction results of CBPT over the two depression detection datasets. From these figures, we know how many depressed or control users has been classified. Here, we use feature importance to analyse which feature significantly affects global depression detection. Feature importance is computed by

$$I^v = \frac{1}{N} \sum_{i=1}^{N} \left| \phi_{X_i}(f) \right|$$

(N is the number of data instances). Figs. 5a and 5c show top 9 significant features for depression detection in the two Twitter datasets. In these two figures, features with large absolute Shapley Values are important. For example, topic2 stands in the most critical position in Fig. 5a and topic2 changes the predicted depression probability by 4% on average for all the instances. Although the feature importance plot is useful, there is no more information beyond the importance. For more information, we use summary plots (Figs. 5b and 5d) to further analyse the significant features. In the summary plots, each point is a Shapley Value $\phi_{X_i}(f)$ corresponding to a feature and an instance. Overlapping points are jittered on the y-axis direction so each row is the distribution of Shapley Values. In Fig. 5b, topic2 with a high feature value (red points) stands for decreasing depression risk and a low value of topic2 (blue points) refers to increasing depression risk. In Table S13-S14, Supplementary C, available online, we show the top 10 words that are the most likely to occur in each LDA topic. Topic2 includes words such as ‘trump’, ‘obama’, ‘russia’ that infers topic2 may be related to ‘politics’. The feature value of topic2 is the occurrence probability of topic2 in the posting texts. If a user posts many tweets on the theme of politics, his/her predicted depression risk will be decreased. Similarly, if a user posts many tweets with emojis that receive many retweets, the user is less likely to be depressed. Depressed users seem to lack of communication with others that depressed users are more likely to post tweets during midnight and their posted tweets are barely retweeted or favourited by other users. And it is an interesting phenomenon that the posting texts of depressed users may involve the content of ‘film’ (topic8) or ‘policy’ (topic6) but without ‘band’ (topic5) information. In Fig. 5d, the most important feature topic4 is related to the theme of ‘mental health’ (shown in Table S14, Supplementary C, available online). In the CLPsych 2015 dataset, depressed users are more likely to undertake the following behaviours: (1) Their posted tweets are related to the topics of ‘mental health’ (topic5) or ‘news’ (topic11) and include many emoticons and negative words. (2) They are young and they do not take many Twitter activities. (3) Their posted tweets may not be favoured by others and their tweets’ content is not related to ‘friend’ (topic19) and ‘autism’ (topic23).

Then, we use the additive force plots to explain why a user is predicted as depressed or control. Using two instances from the TTDD dataset, Fig. 6a is the prediction visualization of a depressed user. In Fig. 6a, the bold text 87% is the predicted depression probability and the base value 34.8% is the classifier’s expectation $\theta_i(f)$ referring to Eq. (2).
Supplementary D, available online. Features pushing the prediction higher are shown in red, while those pushing the prediction lower are shown in blue. For example, the emoji number of this user is 0 which is lower than the average value 0.34 (shown in Table S2, Supplementary A, available online) and it contributes 8% probability to the depression prediction. The total post feature (= 612 that is larger than 457.31) reduces the predicted risk about 4%. This supports our finding in Figs. 5a and 5b that few emojis lead to higher predicted depression risk and posting many tweets leads to less risk. Similarly, for a control user shown in Fig. 6b, this user’s posting content may not be relevant to ‘politics’ (topic2=0.03 that is less than 0.11) that increases the depression risk by 1%. This user’s tweets are frequently retweeted by others (retweet_count=5064 that is over 1843.14) and this behaviour decreases the user’s predicted depression risk. The predicted depression probability for the control user drops from the base probability 34.8% to 23%.

Finally, we use the dependence plots to show the detailed interpretation of the features’ impacts. Fig. 7 includes 6 dependence plots for the most important three features with their most interactive features in the two datasets. The interactive feature can be selected arbitrarily and we decide the most interactive features depending on Eq. (6), Supplementary D, available online. This equation calculates the correlation coefficient between the Shapley Value of the target feature and the values of the other features. In Fig. 7a, the predicted depression risk decreases with the increasing of the values of topic2 and emojis. This suggests that posting tweets on the theme of politics with many emojis leads to lower predicted depression risks and vice versa. In Fig. 7b, topic2 is also the most interactive feature of emojis. This figure shows a similar trend to Fig. 7a. In Fig. 7c, the predicted depression risk shows a decreasing value at total post=400. This suggests that control users are more likely to post many tweets and share politics news than the depressed users. Similarly, from Figs. 7d and 7f, we observe that posting tweets about ‘mental health’ (topic4) and ‘news’ (topic11) is proportionally related to the predicted depression risk. Depressed users’ tweets are hard
to receive favourites from others. The predicted depression risk for the Twitter users is decreasing at age=23 and using the positive or negative words will change the depression risk of the users. By the above feature dependence analysis, we have shown the influences of the feature interactions on the classifier’s predicted depression probability and revealed the difference of the online behaviours between the depressed and control users.

7 Conclusion

In this paper, we have made an attempt to automatically identify potential Twitter depressed users. As we have known, most of the established works mainly focused on exploring new features of depression behaviours whilst ignoring the fitness of the classification models. Considering the complexity of Twitter data, in order to improve the robustness of the decision tree based estimator, we proposed a novel resampling weighted pruning algorithm which dynamically determines optimal depths/layers and leaves of a tree model. Taking into account the “hardness” of different misclassified samples, we also proposed a cost-sensitive boosting structure to hierarchically update the instances’ weights in the pruned trees. We combined the proposed pruning process with the novel cost-sensitive boosting structure within an ensemble framework, namely Cost-sensitive Boosting Pruning Trees (CBPT) to classify control and depressed users.

CBPT outperformed the other depression detection frameworks in the two Twitter datasets. In the meantime, we conducted the convergence analysis of our proposed CBPT through comprehensive experiments. Moreover, we utilised three UCI datasets to evaluate the classification ability of our method quantitatively, which shows our method performs better than the other SOTA boosting algorithm. We then integrated CBPT with TreeSHAP in order to explain the predicted depression risks of Twitter users by investigating the contribution of each feature to the prediction. We used three different types of figures, i.e., additive force plot, summary and dependence plots, to explain the contributions of individual features to the predicted depression risks.

Taking a close look at the above experimental results, we found that the features extracted from the tweet content were really important for depression prediction. Features including LDA topics, negative/positive words and emojis play a key role in online depression risk detection. In the future, we will develop a robust topic model methodology to summarise posting text content of depressed users with clearly explainable topics. We will also attempt to mine similar information over other social networks, e.g., Facebook, Instagram, and Tumblr, for sentiment analysis.

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