RADE: RESOURCE-EFFICIENT SUPERVISED ANOMALY DETECTION USING DECISION TREE-BASED ENSEMBLE METHODS

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ABSTRACT

Decision-tree-based ensemble classification methods (DTEMs) are a prevalent tool for supervised anomaly detection. However, due to the continued growth of datasets, DTEMs result in increasing drawbacks such as growing memory footprints, longer training times, and slower classification latencies at lower throughput. In this paper, we present, design, and evaluate RADE - a DTEM-based anomaly detection framework that augments standard DTEM classifiers and alleviates these drawbacks by relying on two observations: (1) we find that a small (*coarse-grained*) DTEM model is sufficient to classify the majority of the classification queries correctly, such that a classification is *valid* only if its corresponding confidence level is greater than or equal to a predetermined classification confidence threshold; (2) we find that in these fewer harder cases where our coarse-grained DTEM model results in insufficient confidence in its classification, we can improve it by forwarding the classification query to one of *expert* DTEM (*fine-grained*) models, which is explicitly trained for that particular case. We implement RADE in Python based on *scikit-learn* and evaluate it over different DTEM methods: RF, XGBoost, AdaBoost, GBDT and LightGBM, and over three publicly available datasets. Our evaluation over both a strong AWS EC2 instance and a Raspberry Pi 3 device indicates that RADE offers competitive and often superior anomaly detection capabilities as compared to standard DTEM methods, while significantly improving memory footprint (by up to $5.46\times$), training-time (by up to $17.2\times$), and classification latency (by up to $31.2\times$).

1 INTRODUCTION

1.1 Background and related work

Supervised anomaly detection includes a wide range of applications such as finance, fraud detection, surveillance, health care, intrusion detection, fault detection in safety-critical systems, and medical diagnosis. For example, anomalies in network traffic could mean that a hacked device is sending out sensitive data to an unauthorized destination; anomalies in a credit card transaction could indicate credit card or identity theft; and, anomaly readings from various sensors could signify a faulty behavior in hardware or a software component. A popular supervised machine learning (ML) solution for anomaly detection is to employ decision-tree-based ensemble classification methods (DTEMs) which rely on either bagging or boosting techniques to improve the detection capabilities, as explained in the following.

Bagging (or bootstrap aggregation) (Breiman, 1996) is used to reduce the classification variance and by that improve its accuracy. Random Forest (RF) (Breiman, 2001) is the most well-known decision-tree-based bagging method, which grows each decision tree according to a random subsample of the features and the data instances, resulting in different trees. Then, a majority vote is used to determine the classification.

Several studies (Zhang & Zulkernine, 2005; Singh et al., 2014; Tavallaee et al., 2009; Hasan et al., 2014) have proposed using RF for supervised anomaly detection. For instance, (Zhang & Zulkernine, 2005) employed RF for anomaly detection by using data mining techniques to select features and handle the class imbalance problem; and, (Singh et al., 2014) provided a scalable implementation of quasi-real-time intrusion detection system.

RF is a popular classifier as it offers many appealing advantages over other classification methods, such as Neural Networks (Ashfaq et al., 2017), Support Vector Machines (Gan et al., 2013), Fuzzy Logic methods (Bridges et al., 2000), and Bayesian Networks (Kruegel & Vigna, 2003). Specifically, RF offers: (1) robustness and moderate sensitivity to hyper-parameters; (2) low training complexity; (3) natural resilience to deal with imbalanced datasets and tiny classes with very little information; (4) embedded feature selection and ranking capabilities; (5) handling missing, categorical and continuous features; (6) interpretability for advanced human analysis for further investigation or whenever such capability is required by regulations (Right to explanation, 2019), *e.g.,* in order to understand the underlying risks. To that end, an RF can be interpreted by different methods, such as (Banerjee et al., 2012).

[1]VMware Research [2]Technion.

All these aforementioned advantages are repeatedly pointed out in the literature via analysis as well as comparative tests (see (Resende & Drummond, 2018; Moustafa et al., 2018; Habeeb et al., 2018) and references therein) especially for intrusion detection (IDS) purposes (Zhang & Zulkernine, 2005; Tavallaee et al., 2009; Hasan et al., 2014), fraud detection (Xuan et al., 2018) and online anomaly detection capabilities (Zhao et al., 2018; Singh et al., 2014).

Boosting. Unlike bagging, boosting primarily reduces classification bias (and also variance). Many popular decision-tree-based boosting methods such as GBDT (Friedman, 2001; Hastie et al., 2009), XGBoost (Chen & Guestrin, 2016), LightGBM (Ke et al., 2017) and AdaBoost (Freund et al., 1996) employ the boosting concept, usually, by using iterative training. For example, in Adaptive Boosting, a weak classifier such as a *stump* is added at each iteration (unlike bagging methods that use fully grown trees) and typically weighted with respect to its accuracy. Then, the data weights are readjusted such that a higher weight is given to the misclassified instances. In Gradient Boosting, a small decision tree (*e.g.,* with 8-32 terminal nodes) is added at each iteration and scaled by a constant factor. Then, a new tree is grown to reduce the loss function of the previous trees. For both methods, the next trees are trained with more focus on previous misclassifications.

Decision-tree-based boosting methods are known to be among the best off-the-shelf supervised learning methods available (Roe et al., 2006; Schapire, 2003; Liu et al., 2017; Roe et al., 2005), achieving excellent accuracy with only modest memory footprint, as opposed to RF that is usually memory bounded. Boosting methods also share many of the aforementioned advantages offered by RF such as natural resilience to deal with imbalanced datasets and tiny classes, embedded feature selection, and ranking capabilities, and handling missing, categorical and continuous features (Jin & Chuang, 2017).

Decision-tree-based boosting methods are also known to be especially appealing for anomaly detection purposes where data is often highly imbalanced (*e.g.,* credit card transactions or cyber-security) (Pfahringer, 2000; Li, 2012). This is mainly because decision-tree-based boosting methods alter their focus between the different iterations on the more difficult training instances. This often produces a stronger strategy to deal with imbalanced datasets by strengthening the impact of the anomalies and, when adequately trained, boosting methods may usually achieve higher accuracy (as well as precision and recall) than a traditional RF classifier. That being said, boosting methods are also more sensitive to overfitting than RF, especially when the data is noisy (Dietterich, 2000). The training of boosting-based methods generally takes much longer than RF, mainly since the trees are built sequentially and compute-intensive tasks such as classification and data weights readjustments take place at every iteration. Moreover, boosting-based methods are harder to tune as compared to RF, as they have more parameters and higher sensitivity to these parameters.

Finally, both bagging (RF) and boosting methods are prevalent tools for supervised anomaly detection with shared and distinct pros and cons, and there is no clear winner in this classification contest as the best classifier often depends on the specific dataset and the application.

1.2 Challenges

In recent years, supervised anomaly detection via DTEMs is becoming extremely difficult. This is because traditional bagging DTEMs (*i.e.,* random forest) classifiers can be highly effective, but tend to be memory bound, and slower at classification (Liaw et al., 2002; Van Essen et al., 2012; Mishina et al., 2015). Furthermore, the classification latency of an RF increases with the RF depth (Asadi et al., 2014). Accordingly, previous work suggested different approaches to tackle the memory and performance drawbacks of RF. The study of (Van Essen et al., 2012) achieves deterministic latency by producing compact random forests composed of many, small trees rather than fewer, deep trees. Other studies (Asadi et al., 2014; Browne et al., 2018) optimize memory-layouts of RF, which reduces cache misses.

On the other hand, boosting DTEMs are slow to train and tune and also admit slower classification as the number of trees increases (Appel et al., 2013; Ravanshad, 2018). Much effort has been made to address these drawbacks. For example, recent scalable implementations of the tree-based gradient boosting methods include: XGBoost (Chen & Guestrin, 2016) that supports parallelism and uses pre-sorted and histogram-based algorithms for computing the best split; LightGBM (Ke et al., 2017) that uses a novel technique of Gradient-based One-Side Sampling (GOSS) to filter out the data instances for finding a split value; CatBoost (Prokhorenkova et al., 2018) that implements *ordered boosting*, a permutation-driven alternative to the classic algorithm and an innovative algorithm for processing categorical features (*e.g.,* giving indices of categorical columns such that it can be encoded by one-hot encoding). For Adaptive boosting (*i.e.,* AdaBoost), several approaches have been suggested as well to accelerate its slow training (Chu & Zaniolo, 2004; Seyedhosseini et al., 2011; Olson, 2017). For example (Seyedhosseini et al., 2011) introduces a new sampling strategy (WNS) that selects a representative subset of the data at each iteration and by that reducing the number of data points onto which AdaBoost is applied.

Nevertheless, both bagging and boosting DTEM methods are challenged by the continuous growth of datasets (Li et al., 2014) in terms of the number of features, data instances, and the increasing demand for lower memory footprints, faster training, and lower classification latency. That is, while a sufficiently large DTEM classifier may offer a satisfactory anomaly detection capabilities when adequately trained, it would typically suffer from at least one of the

Table 1: Baseline DTEM models. Number of trees and tree depth limitations for each DTEM classifier and dataset (RF is trained without tree depth limitation).

	KDD	CCF	FC
RF	$C(150, None)$	$C(85, None)$	$C(80, None)$
GBDT	$C(1400, 5)$	$C(600, 5)$	$C(800, 5)$
XGBoost	$C(450, 3)$	$C(500, 3)$	$C(2000, 3)$
LightGBM	$C(1000, 5)$	$C(1600, 5)$	$C(2800, 3)$
AdaBoost	$C(700, 3)$	$C(1100, 2)$	$C(1000, 3)$

following drawbacks: (1) large memory footprint; (2) long training (which also incurs high energy consumption); (3) high classification latency and low classification throughput. Overcoming these drawbacks is essential for efficient DTEM-based anomaly detection systems that are required to have the ability to quickly train a proper classifier in a timely manner and to offer low classification latency and high throughput at reasonable memory footprints and costs.

1.3 Contributions

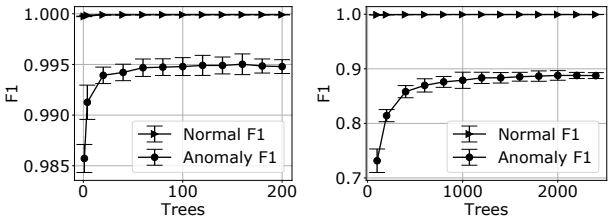
In this paper, we present RADE, which addresses the aforementioned drawbacks of DTEM methods. RADE is orthogonal to the discussed bagging and boosting techniques and can augment them to form more efficient DTEM classifiers. We implement and evaluate RADE for RF, XGBoost, AdaBoost, GBDT, and LightGBM.

The design of RADE mainly relies on the two following observations, which are further detailed in Section 2:

(1) We find that a small (*coarse-grained*) DTEM model is sufficient to classify the majority of the classification queries correctly. To that end, we define a confidence level threshold, such that a classification is considered to be *valid* only when its classification confidence level is higher than or equal to this given threshold.

(2) We find that in these fewer harder cases where our coarse-grained DTEM model exhibits insufficient confidence in its classification, we can improve it by forwarding the classification query to one of expert DTEM (*fine-grained*) models, which is explicitly trained for that particular case.

Finally, in Section 5, we present evaluation results over three publicly available datasets and on a strong AWS EC2 instance as well as on a Raspberry Pi 3 device. The results are consistent and indicate that RADE always offers competitive and often superior anomaly detection capabilities as compared to the standard DTEM methods. For Bagging (RF), RADE significantly improves the training-time (by up to $6.42\times$), classification latency (by up to $7.23\times$), and memory consumption (by up to $5.46\times$); For Boosting (*e.g.,* XGBoost and AdaBoost), RADE significantly improves the classification latency (by up to $31.2\times$) and training time (by up to $17.2\times$), while being competitive in model memory footprint (always in the range of $[0.64\times, 2.92\times]$).



(a) RF over KDD. (b) XGBoost over FC.

Figure 1: Baseline tuning examples by sweeping over the number of trees. (a) The best F_1 score for the RF classifier over the KDD dataset is achieved for 150 trees with no depth limitation, *i.e.,* $C(150, None)$. (b) The best F_1 score for XGBoost classifier over the FC dataset is achieved for 2000 trees with depth limitation of 3, *i.e.,* $C(2000, 3)$.

2 RADE Preliminaries

2.1 Baseline DTEM models

We evaluate RADE and quantify its benefits by comparing it to standard DTEM models we term *baseline* models. Specifically, we define a baseline model for three different datasets (KDD (Machine Learning Repository - UCI, 1999), Credit-Card Fraud (CCF) (Machine Learning Group - ULB, 2013), and Forest Cover (FC) (Machine Learning Repository - UCI, 1998)) and for five different DTEM classifiers (RF (Breiman, 2001), GBDT (Friedman, 2001; Hastie et al., 2009), XGBoost (Chen & Guestrin, 2016), LightGBM (Ke et al., 2017) and AdaBoost (Freund et al., 1996)). For each dataset and DTEM classifier, we choose the baseline model for comparison by sweeping over different parameters and conducting 5-fold cross-validation for each measurement. Figure 1 shows two such examples. In these specific examples, we depict the F_1 score as a function of the number of trees for the RF model over the KDD dataset (1(a)) and for the XGBoost model over the FC dataset (1(b)). Note that we conduct sweeps over the number of trees for different parameters (*e.g.,* class/sample weights for RF, the number of features to consider for a split, tree depth limitations, learning rate for XGBoost) and in these examples, the other parameters are already chosen accordingly.

Remark. Interestingly, these two sweeps already point out the weaknesses of bagging and boosting methods: (1) The sweep in Figure 1(a) lasted for 699 seconds and required 205 MB, whereas a similar sweep for XGBoost (over KDD) lasted as much as 14865 seconds but required only 8 MB; (2) Similarly, the sweep in Figure 1(b) lasted for 25442 seconds and required 47 MB, whereas a similar sweep for RF (over FC) lasted only 425 seconds but required 340 MB[1].

ML performance metric. In this paper, we use *per-class* F_1 score to quantify the anomaly detection capabilities of

[1]These specific baseline tuning examples were conducted on an Intel(R) Core(TM) i7-7700 CPU @ 3.60GHz with 4 Cores and 8 Logical Processors.

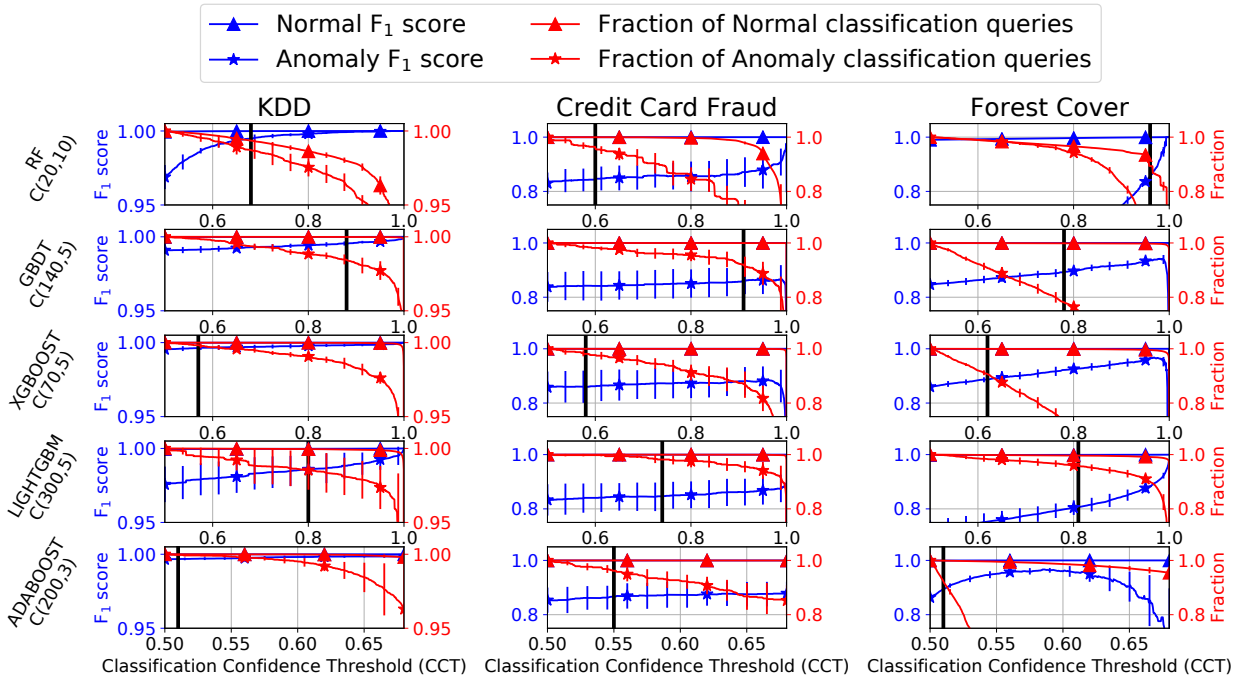


Figure 2: The useful classification fraction and its resulting F_1 score by a small (coarse-grained) model, when a classification is *valid* only if its confidence level is greater than or equal to a given classification confidence threshold (CCT). Our observation is that most classifications can be achieved by a coarse-grained model, with a similar/higher resulting F_1 score as compared to the F_1 score achieved by a much bigger model – termed baseline model[4]. The vertical lines indicate the lowest CCT for each dataset and model such that the resulting F_1 score exceeds the F_1 score by a baseline model (see Table 1 for details). Note that any other CCT value can be set according to the desired tradeoff between the useful classification fraction and its resulting F_1 score. Demonstrated for KDD (Machine Learning Repository - UCI, 1999), Credit Card Fraud (CCF) (Machine Learning Group - ULB, 2013), and Forest Cover (FC) (Machine Learning Repository - UCI, 1998) datasets, over five different DTEM classifiers, RF (Breiman, 2001), GBDT (Friedman, 2001; Hastie et al., 2009), XGBoost (Chen & Guestrin, 2016), LightGBM (Ke et al., 2017) and AdaBoost (Freund et al., 1996). In all evaluations, we use a 5-fold cross validation and depict the mean value and variance.

ML models since this score takes into account the imbalanced nature of the datasets in anomaly detection use-cases. Nevertheless, we also consider the Area Under the Curve (AUC) and Average Precision (which is more suitable for skewed datasets) metrics, and obtain similar results.

Classifier configuration. For ease of exposition, we denote a classifier with T trees, each limited to a depth of D, by $C(T, D)$. A classifier without a depth limitation is denoted by $C(T, None)$. Table 1 summaries the baseline DTEM classifiers which we use throughout the paper.

2.2 Observations

In this work, we target binary supervised anomaly-detection classification with *Normal* and *Anomaly* imbalanced classes, and discuss multi-class anomaly detection as a future direction/extension of RADE in Section 6. In the following, we describe the two main aforementioned observations which our solution is based on.

Observation 1: A small DTEM model can classify most of the classification queries with a high F_1 score.

Figure 2 exemplifies via three datasets (KDD, CCF and FC. Further details are in Section 5.1), and over five DTEMs (RF, GBDT, XGBoost, LightGBM, and AdaBoost) that a small DTEM model, which we term *coarse-grained* model, can be used to correctly classify the majority of classification queries (but not necessarily all) by requiring a sufficiently high classification confidence level[2]. That is, the classification result of the coarse-grained model is *valid* only if its corresponding confidence level is greater than or equal to a predetermined classification confidence threshold (denoted by CCT), rather than simply accepting any classification confidence[3]. We empirically find that this approach of setting a higher CCT value to make a valid classification,

[2]For a DTEM classifier, the classification and its confidence level is determined by the classification distribution vector. For example, if the classification output of an instance is (Normal=0.78, Anomaly=0.22) that means the instance is classified as Normal with a classification confidence level of 0.78.

[3]For example, if the prediction output of a sample is (Normal=0.83, Anomaly=0.17) and CCT= 0.9 that means the classification is not valid and this query requires further attention as we later detail in Section 3.

results in a high fraction of the data instances being valid classifications with a high F_1 score for both Normal and Anomaly classes.

Specifically, as can be seen in Figure 2, the fraction of the valid classifications (out of the total data instances) reduces as CCT increases, and their respective F_1 score increases[4] since only the classifications with a higher confidence level (*i.e.,* valid) are being considered[5]. Furthermore, the fraction of the Normal data instances is significantly higher than the Anomaly fraction as CCT increases. Intuitively, this is because the Anomaly labeled instances are harder to classify, as there are significantly fewer Anomaly instances than the Normal instances available for training.

We have found this observation to be consistent for all tested datasets. These include the three datasets discussed in this paper, as well as a Bankruptcy data set (Machine Learning Repository - UCI, 2013; Zięba et al., 2016), a Shuttle data set (Machine Learning Repository - UCI, 1988) and different synthetic datasets generated by the scikit-learn machine learning Python package (Pedregosa et al., 2011).

As we later discuss and demonstrate, any CCT value can be set according to the desired tradeoff between the useful classification fraction and its resulting F_1 score. The vertical black lines in Figure 2 indicate the lowest CCT for each dataset and classifier such that the resulting F_1 score of the valid classifications of both the Normal and Anomaly classes exceed the total F_1 score of its corresponding baseline model, as detailed in Table 1 (for the baseline models, a valid classification is any classification with a confidence level of a least 0.5, *i.e.,* all classification queries are valid and considered). Finally, we provide two examples to clarify the findings depicted by Figure 2.

Example 1. By setting CCT=0.995 (instead of the usual 0.5) when using the RF model, $C(20, 10)$, for the CCF dataset, we obtain that a fraction that accounts for 51.6% of the Normal data instances is classified with F_1 score of ≈ 0.99991; and a fraction that accounts for 45.5% of the Anomaly data instances is classified with F_1 score of ≈ 0.943. Whereas, the corresponding baseline DTEM model, $C(85, None)$, achieves F_1 score of ≈ 0.99974 and ≈ 0.8344, respectively.

Example 2. By setting CCT=0.99 (instead of the usual 0.5) when using the XGBoost model, $C(70, 5)$, for the KDD dataset, we obtain that a fraction that accounts for 99.8% of the Normal data instances is classified with F_1 score of ≈ 0.99993; and a fraction that accounts for 94.2% of the Anomaly data instances is classified with F_1 score of ≈ 0.9992. Whereas, the corresponding baseline DTEM model, $C(450, 3)$, achieves F_1 score of ≈ 0.99993 and ≈ 0.9962, respectively.

Observation 2: Train expert (fine-grained) classifiers to succeed specifically where the coarse-grained model is not sufficiently confident.

When applying the approach suggested by the previous Observation 1, we remain with a small fraction of the data instances without a valid classification by the coarse-grained model due to an insufficient classification confidence level (*i.e.,* queries for which the top-1 class probability is lower than CCT). These queries are the harder data instances and, most importantly, as depicted in Figure 2, contain most of the anomalies as the CCT increases.

Our second main observation is that we can leverage the classification distribution vector of the coarse-grained model over the *training data* to: (1) *filter most of the training data* by using a training confidence threshold (TCT), and to (2) train expert classifiers, which we term *fine-grained* models, that are *trained to succeed specifically where the coarse-grained model is not sufficiently confident and is more likely to make a classification mistake*. The training dataset of each fine-grained classifier is defined according to TCT and the resulting classification distribution vectors of the coarse-grained model (see Section 3 for more details).

As we show in Section 5.2, these training datasets of the fine-grained classifiers are tailored such that they focus on the harder data instances and improve the Normal to Anomaly ratio of the labeled instances as compared to the training dataset of the coarse-grained and baseline classifiers. As a result, we find that the fine-grained models achieve better F_1 score for the low-confidence data instances.

Furthermore, these tailored training datasets are much smaller as compared to the training sets of the coarse-grained and baseline classifiers, which in turn significantly reduces the required training time (and hence the corresponding energy consumption). This attribute is especially appealing for the boosting methods (see Section 5).

2.3 The intuition behind RADE

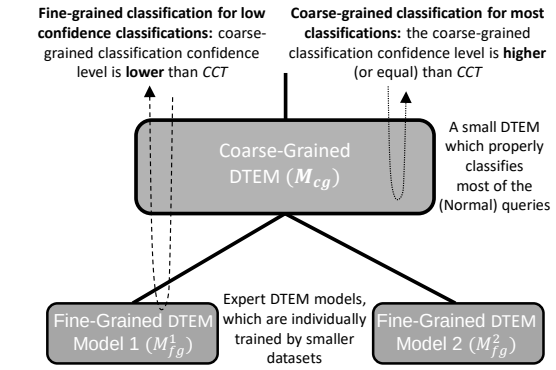
So far, we have mainly discussed the ML-performance of RADE and why, intuitively, it is expected to result in a high F_1 score. Now we discuss further intuition to why RADE also results in lower memory footprint, lower training time (and hence lower energy consumption) and lower classification latency, as compared to the baseline models.

The training time complexity of DTEM methods depends on the size of the training dataset (*i.e.,* the number of training instances), the number of features, the number of trees and their depth limitations (if there are any). Whereas, the classification latency mostly depends on the model size (*i.e.,* the number of trees, and their depths).

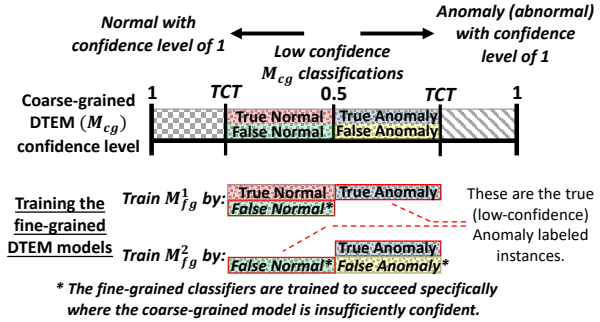
Clearly, the smaller model size of a coarse-grained classi-

[4]Unless the CCT is set too high, such that the fraction of valid classifications, especially anomalies, drops to nearly zero and the remaining few instances may admit a high classification variance (See XGBoost over CCF in Figure 2 for example). Such CCT values are not reasonable operating points for RADE.

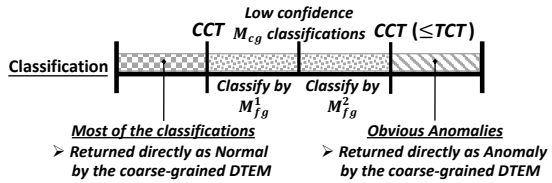
[5]Our usage of a classification confidence level is inherently different from the threshold used to produce a ROC curve. That is, when producing a ROC curve, the threshold only determines the result of a classification query and not whether it is valid.



(a) RADE architecture.



(b) RADE confidence level driven training.



(c) RADE confidence level driven classification.

Figure 3: RADE architecture - a small (coarse-grained) model and two expert (fine-grained) models. The training confidence threshold (TCT) at the coarse-grained model determines the training data for each fine-grained classifier. For classification, the classification confidence threshold (CCT) at the coarse-grained model determines whether a classification query takes the short or the long path and which fine-grained model is queried for the latter case.

fier directly improves all of the criteria mentioned above. Additionally, as mentioned, the fine-grained classifiers are being trained by smaller datasets, which reduces their training time, and, often, their size. Indeed, our evaluation in Section 5 shows that the size of the fine-grained models is smaller as compared to their corresponding baseline model for all tested data sets and classification methods.

Essentially, when considering a RADE model (*i.e.,* both the coarse-grained and fine-grained models), the classification latency of RADE equals to a weighted average of the latencies according to the fraction of the classifications that are served by the coarse-grained and fine-grained models. Since the coarse-grained model serves most of the classifications, the averaged classification latency is expected to significantly improved as compared to the baseline model. Furthermore, our evaluation shows that the worst-case classification latency of RADE (*i.e.,* the latency of a query that takes the longest path of coarse-grained model and then the slowest fine-grained model) is also competitive and often lower than the latency of its corresponding baseline model (for more details, see the evaluation in Section 5).

On the other hand, the training time and model size of RADE equal to the corresponding sums of the coarse-grained and fine-grained models. Nevertheless, as presented in Section 5, our evaluation indicates that RADE reduces the memory footprint and training time, as compared to the baseline models.

To summarize, both the coarse-grained and fine-grained models contribute to the overall improvements of RADE, in the following ways: The coarse-grained model is (1) based on a small classifier and, (2) serves most of the classification queries. The fine-grained models are (1) being trained by smaller data sets, (2) smaller as compared to the corresponding baseline and, (3) serve only a small fraction of the classification queries.

3 RADE

Training. Algorithm 1 describes the procedure for training a RADE model. It begins with the training of a coarse-grained model (denoted by M_{cg}) using the entire labeled dataset. Next, we train the fine-grained models (denoted by M^i_{fg} for fine-grained model i). To that end, we classify the labeled dataset by the coarse-grained model (line 5). Then, if the confidence level of the predicted top-1 class (*i.e.,* $max(d_x)$) is lower than the given training threshold (TCT), the labeled data instance is forwarded to both experts if its label is Anomaly (lines 7-9) or otherwise to a single fine-grained model according to the prediction made by M_{cg} (lines 11-15). Notice that in lines 11-15, the data instances are forwarded *according to their low-confidence coarse-grained classification, and not according to their labels*. The reason is that we train the fine-grained models to succeed specifically where the coarse-grained model is insufficiently confident and is more likely to make a mistake. More specifically, as illustrated in Figure 3(b), the data instances that are forwarded to fine-grained model 1 contain: (1) *all* low confidence Anomaly instances and, (2) low confidence Normal instances that are correctly classified by the coarse-grained model. Intuitively, this model becomes an expert in distinguishing between Normal instances that are correctly classified by the coarse-grained model and Anomaly instances. Likewise, the data instances that are forwarded to fine-grained model 2 contain: (1) *all* low confidence Anomaly instances and, (2) low confidence Normal instances that are misclassified by the coarse-grained model. Intuitively, this model becomes an expert in distinguishing between misclassified Normal instances by the

coarse-grained model and Anomaly instances.

The Anomaly class is significantly smaller (usually by orders of magnitude) than the Normal class in terms of the number of instances, and its low-confidence subset is even smaller. This fact results in two potential drawbacks, which we mitigate by the duplication of the low-confidence Anomaly labeled instances to both fine-grained models (lines 8-9), as explained in the following:

Less accurate Anomaly coarse-grained classification: Since the coarse-grained model is trained using a rather small number of Anomaly instances as compared to the number of Normal instances, its classifications over these instances are very noisy with many misclassifications as compared to the Normal instances (see Figure 2). Namely, the classification distribution vector over these instances has a significant variance, which is even more severe for the low-confidence Anomaly subset. This makes the classification of the coarse-grained model as to which fine-grained model we need to send a specific low-confidence Anomaly instance less reliable (unlike for the Normal instances).

Increased overfitting likelihood by the fine-grained models: Due to the small cardinality of the low-confidence subset of the Anomaly instances, it is more likely for a fine-grained classifier to receive a non-sufficient number of such instances for training. This, in turn, increases the likelihood of overfitting the model. That is, it is more likely for the training of a fine-grained classifier to terminate in a state in which it has a nearly perfect F_1 score for the low-confidence subset of the Anomaly instances that were forwarded by the coarse-grained model for its training, but this fine-grained model is likely to be less accurate at classification of a low-confidence Anomaly instance that may have been sent to the wrong fine-grained model and thus is more likely to be too different from other labeled instances this fine-grained classifier was trained on.

Therefore, by forwarding all the low-confidence subset of Anomalies to both experts, as we empirically find in our evaluations, reduces the likelihood of both drawbacks and makes the fine-grained models better experts for those queries in which the coarse-grained model is more likely to make a classification mistake (*i.e.,* Observation 2).

Note that this *duplication* (*i.e.,* lines 8-9) results in a very low overhead in terms of the number of data instances used for the fine-grained models training (see Table 2).

Classification. Algorithm 2 describes the procedure for a classification by RADE, and Figure 3(c) illustrates it. First, we classify an arriving data instance by the coarse-grained model (lines 1-2). Whenever the resulting confidence level of the top-1 classification is greater than or equal to the classification confidence threshold, CCT, the classification by the coarse-grained model is *valid* and therefore returned (line 4). As shown in Figure 2, we empirically find that most of the data instances result in a high confidence level. Therefore, since the size of the coarse-grained model is small,

Algorithm 1 RADE training

Input: Labeled training data set X, confidence level TCT.
1: train M_{cg} using X
2: set: $data[\text{fg}_1] = \emptyset$
3: set: $data[\text{fg}_2] = \emptyset$
4: for each $x \in X$:
5: obtain coarse-grained distribution: $d_x = M_{cg}(x)$
6: if $max(d_x) <$ TCT:
7: if $x.label == Anomaly$:
8: update: $data[\text{fg}_1].append(x)$
9: update: $data[\text{fg}_2].append(x)$
10: else:
11: classify: $y = argmax(d_x)$
12: if $y == Normal$:
13: update: $data[\text{fg}_1].append(x)$
14: else:
15: update: $data[\text{fg}_2].append(x)$
16: train M^1_{fg} using $data[\text{fg}_1]$
17: train M^2_{fg} using $data[\text{fg}_2]$

Algorithm 2 RADE classification

Input: Unlabeled data point x, confidence level CCT.
1: obtain coarse-grained distribution: $d_x = M_{cg}(x)$
2: classify: $y = argmax(d_x)$
3: if $max(d_x) \geq$ CCT:
4: return y
5: else:
6: $y == Normal\ ?\ c = 1 : c = 2$
7: obtain fine-grained distribution: $\bar{d}_x = M^c_{fg}$
8: classify: $\bar{y} = argmax(\bar{d}_x)$
9: return $\bar{y}$

these classification instances experience an extremely low-latency and high-throughput classification. The remaining small fraction of the data instances whose coarse-grained classification is not valid (*i.e.,* which their resulting confidence level is lower than CCT) is forwarded to one of the fine-grained models, which is chosen according to the coarse-grained classification (lines 6-9). Specifically, if the coarse-grained low-confidence classification is Normal, then the instance is forwarded to fine-grained model 1 which is trained to distinguish between Normal instances that are correctly classified by the coarse-grained model and Anomaly instances (see Figure 3(b)). Likewise, if the coarse-grained (low-confidence) classification is Anomaly, then the instance is forwarded to fine-grained model 2 which is trained to distinguish between Normal instances that are misclassified by the coarse-grained model and Anomaly instances.

Putting it all together. Figure 3 depicts a high-level architecture of RADE, and the training and classification data-forwarding schemes. We may use *different* confidence level thresholds for the fine-grained models training (TCT) and the classification/anomaly detection (CCT), such that TCT$\geq$CCT. The intuition for why it may be of interest to set TCT$>$CCT, is that it allows to train the fine-grained

models with a bigger subset of the labeled data instances as compared to the classification subset that is forwarded to them. Tuning TCT, as we empirically find in our evaluations, often improves the anomaly detection capabilities (in terms of F_1 score) for a modest price in training time and fine-grained model sizes.

Intuitively, the fine-grained models provide better classification and hence better anomaly detection for the uncertain classifications than the coarse-grained model for the following reasons: (1) we allow the fine-grained models to have more resources as compared to the coarse-grained model (see Section 5.2 for more details); (2) the fine-grained classifiers are trained by a much smaller fraction of the labeled training data. Essentially, each fine-grained model becomes an expert for its corresponding labeled data fraction, which represents the uncertain (and some of the wrong) classifications by the coarse-grained model. Note that when a classification query is forwarded to a fine-grained model, it is solely determined by this fine-grained model.

RADE model. For ease of exposition, we define a specific configuration of a RADE model by a tuple $R(C(T_{cg}, D_{cg}), C(T_{fg}, D_{fg}), \text{CCT}, \text{TCT})$, that states the size limitation of the coarse-grained model followed by the size limitation of the fine-grained models and finally the classification and training confidence thresholds.

4 Implementation

RADE implementation is written in Python 3.6 and is based on the *scikit-learn* library[6] (Pedregosa et al., 2011). RADE can augment any scikit-based DTEM classifier. Specifically, we execute RADE for internal scikit classifiers (RandomForest (Scikit - RF, 2019), GradientBoosting (Scikit - GBDT, 2019), and AdaBoost (Scikit - ADABOOST, 2018)), as well as for Python packages (lightgbm-v2.2.3 (PyPI, LightGBM, 2019), and xgboost-v0.90 (PyPI, XGBoost, 2018)).

5 Evaluation

5.1 Datasets

As mentioned, we use three different datasets, where all are widely used, publicly available, and reproducible. To establish consistency for RADE, we chose the dataset such that they are all from different areas and use-cases as well as with different levels of skewness (*i.e.,* the Normal to Anomaly number of instances ratio).

KDD (Machine Learning Repository - UCI, 1999). This dataset is a popular benchmark and is widely used for evaluation of IDS systems (Dhanabal & Shantharajah, 2015; Kayacik et al., 2005; Sabhnani & Serpen, 2003). It was used for The Third International Knowledge Discovery and Data Mining Tools Competition in which the task was to build a network intrusion detector. This database contains a standard set of data to be audited, which includes a wide variety of intrusions simulated in a military network environment. In our evaluation, we treat all intrusions (*e.g.,* DoS, Probe, R2L) as Anomalies (24.389%) and all non-hostile connections as Normal.

Credit Card Fraud (CCF) (Machine Learning Group - ULB, 2013). This is a popular dataset that is used for anomaly and fraud detection benchmarking. (Dal Pozzolo et al., 2015; Carcillo et al., 2017; Lebichot et al., 2020; Carcillo et al., 2019; Dal Pozzolo, 2015). The datasets contains transactions made by credit cards in September 2013 by european cardholders. This dataset presents transactions that occurred in two days, with frauds which we treat as Anomalies (0.172%) where all the rest are legitimate transfers and treated as Normal class.

Forest Cover (FC) (Machine Learning Repository - UCI, 1998). This dataset is used in predicting forest cover type from cartographic variables (Blackard, 2000; Gama et al., 2003; Oza & Russell, 2001; Obradovic & Vucetic, 2004). This study includes four wilderness areas located in the Roosevelt National Forest of northern Colorado. Class 2 is considered as Normal, and class 4 as Anomaly (0.9%).

5.2 Tuning RADE

The tuning of a RADE classifier starts by identifying a set of sensible candidate hyperparameters for the coarse-grained model. Recall that we want a small coarse-grained model that can make valid classifications for most of the data instances with a high F_1 score (*e.g.,* Figure 2).

To that end, a set of such sensible hyperparameters may be derived by looking at known default configurations and thumb rules for a specific standard full-sized classifier and for similar datasets (if such are known) and considering smaller sized options such that the resulting coarse-grained model will be smaller than a standard full-sized classifier by some constant factor (*e.g.,* $5\times$).

The candidate hyperparameters for the fine-grained models are then chosen similarly but by considering larger sizes (*i.e.,* number of trees, depth limitations) varying from the coarse-grained and up to a standard model size.

Next, we need to consider candidate CCT and TCT values. The set of interest is always $0.5 \leq \text{CCT} \leq \text{TCT} \leq 1$ sampled according to some granularity (*e.g.,* 0.05).

Finally, once we have our grid of sensible hyperparameter configurations for RADE, we perform iterations of our 5-fold cross-validation process, each time using different model settings from this predetermined set. This grid-search tuning process is no different from standard practice.

Clearly, these parameters are not guaranteed to be optimal. With that said, finding satisfactory hyperparameters often requires an extensive grid-search, like any other classifier.

Example. We next demonstrate how CCT and TCT affect the F_1 score, classification latency, training time, and model size. Figure 4(a) presents these metrics vs. different values of CCT (with TCT=CCT for simplicity) of a RF-based

[6] v0.21.3 - released on July 30, 2019 (current stable version).

$R(C(20,10), C(25,10), -, -)$ for the CCF dataset. We identify two CCT values, CCT=0.915 and CCT=1, that achieve the highest Anomaly F_1 (marked in the graph). Notice that, CCT=1 results in forwarding *most* of the test dataset to the fine-grained models, which in turn increases the classification latency. Moreover, as TCT increases, a higher fraction of the training-data is being forwarded to the fine-grained models, which in turn increases both the model size and training-time.

Table 4(b) also presents the Normal to Anomaly ratio of the training data instances that are forwarded to each of the fine-grained models. As can be seen, this ratio is further improved as compared to the original dataset ratio (581.4) for fine-grained model 1 with CCT=0.915 (while CCT=1 results in a ratio similar to the original one). Notice that, for fine-grained model 2, the ratio is lower than one, which means that the model is being trained with more Anomaly-labeled instances than Normal-labeled ones. Additionally, the table presents these attributes for $R(C(20,10), C(25,10), 0.5, 0.5)$ model, which is essentially identical to $C(20,10)$ (a smaller baseline model), that returns *all* of the data instance classifications *only* by the coarse-grained model. This RADE model demonstrates that the fine-grained models are essential to achieve sufficient Anomaly F_1, even when their total test dataset fraction is relatively low (*e.g.,* 2.34% for CCT=0.915).

A better CCT and TCT configuration for this RADE model, $R(C(20,10), C(25,10), 0.995, 1.0)$, is achieved by the grid-search process mentioned above, as further detailed next in Table 2.

5.3 RADE vs. standard methods

We compare RADE to the baseline models over an AWS m5d.16xlarge EC2 instance with Ubuntu 16.04 OS (Amazon EC2, 2019), and summarize the evaluation results in Table 2. The results of RF, XGBoost and AdaBoost are summarized, while similar improvements are obtained for GBDT and LightGBM. For each classifier and dataset, we present results for the baseline model and two different configurations of RADE. We rely on 5-fold cross-validation and report the mean values.

5.3.1 Bagging - Random Forest

Anomaly detection. For all three datasets RADE exhibits competitive or superior F_1 scores as compared to the baseline[7]. Specifically, the results are somewhat similar for the KDD and CCF; whereas for FC, both RADE configurations result in an advantage of $\approx +2.4\%$ in Anomaly F_1.

Model size. All RADE model sizes are notably smaller than their corresponding baseline model. For example, for KDD, $R(C(10,10), C(20,20), 0.98, 0.995)$ is $5.46\times$ smaller than $C(150, None)$.

Training time. For all three datasets, the training time of RADE is significantly lower. For example, it is $6.42\times$ faster for KDD. These lower training times come in line with the smaller size of the coarse-grained model as compared to the baseline and the small fractions of the training data that are used for the training of the fine-grained models.

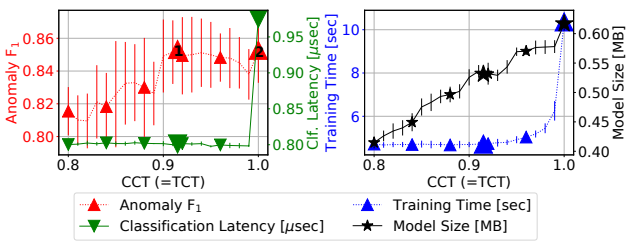
Classification latency. The improvement of RADE over the baseline is consistent and is up to $7.23\times$ faster due to the smaller latency introduced by the coarse-grained model. Even when considering the worst-case classification latency for RADE (*i.e.,* a query that takes the path of coarse-grained model and then the slowest fine-grained model) RADE is still competitive. The non-negligible difference between the average and worst-case classification latency for RADE falls in line with the small fractions of queries taking the long path (*e.g.,* 5.56% for both fine-grained models for KDD).

5.3.2 Boosting - XGBoost and AdaBoost

Anomaly detection. For all three datasets, RADE exhibits competitive or superior anomaly detection capabilities as compared to the baseline. For example, for XGBoost over FC, RADE configuration achieves a better Anomaly F_1 by $+0.5\%$; and for AdaBoost over FC, RADE configurations improve the Anomaly F_1 by $\approx +1\%$ and $+0.6\%$.

Model size. XGBoost model sizes of RADE and the baseline are competitive. AdaBoost model sizes of RADE are up to $2.92\times$ larger than the baseline. This is of less concern

[7] As mentioned, we consider F_1 score as the ML performance measure for anomaly detection (*i.e.,* imbalanced datasets). Nevertheless, we also evaluate RADE models for AUC and Average Precision and reach similar conclusions.



(a) How CCT and TCT(=CCT) affect different metrics. The two CCT values that achieve the highest Anomaly F_1 are marked.

Index	CCT	Anomaly F_1	Fine Grained (FG) train data fraction	FG Nor./Anom. train data ratio $[M^1_{fg}, M^2_{fg}]$	FG total test data fraction
-	0.5	0.810	0.0%	nan, nan	0.0%
1	0.915	0.853	2.32%	45.11, 0.348	2.34%
2	1.0	0.852	98.4%	567.7, 0.136	98.2%

(b) RADE attributes for the marked CCT values in (a), and for CCT=0.5 – *i.e.,* when *all* coarse-grained model classifications are considered as valid. Note that the original Normal to Anomaly instance ratio of CCF is 581.4, and the Anomaly F_1 of the corresponding baseline model is 0.845471.

Figure 4: How CCT and TCT(=CCT) affect RADE, demonstrated with RF-based $R(C(20,10), C(25,10), -, -)$ for CCF dataset.

Table 2: Comparison among two RADE configurations to the baseline over three classification DTEM methods, each with three different datasets. All results are obtained using 5-fold cross-validation. RADE achieves competitive and often superior F_1 score with lower training time, classification latency, and superior (for bagging) or competitive (for boosting) model size.

Classifier	Dataset	#	Model	Normal F_1	Anomaly F_1	Model size [MB]	Train time [s]	Fine-grained train data % [fg1, fg2]	Classification latency [μs]	RADE worst-case classification latency [μs]	Fine-grained test data % [fg1, fg2]
RF	KDD	1	Baseline – $C(150, None)$	0.999913	0.995190	5.57	22.5	–	9.4	–	–
		2	$R(C(10,10), C(20,20), 0.98, 0.995)$	0.999910	0.995028	1.02	3.5	9.55%, 0.57%	1.3	6.9	5.19%, 0.37%
		3	$R(C(10,10), C(35,20), 0.98, 0.98)$	0.999911	0.995091	1.54	3.6	5.38%, 0.35%	1.3	10.1	5.19%, 0.37%
	CCF	4	Baseline – $C(85, None)$	0.999759	0.845471	2.01	75.6	–	6.2	–	–
		5	$R(C(20,10), C(30,20), 0.94, 0.953)$	0.999733	0.840198	0.82	20.3	6.82%, 0.09%	1.9	4.7	3.72%, 0.06%
		6	$R(C(20,10), C(25,10), 0.995, 1.0)$	0.999756	0.854553	0.63	40.7	97.57%, 0.20%	2.1	3.4	41.78%, 0.09%
	FC	7	Baseline – $C(80, None)$	0.999379	0.859186	9.95	16.7	–	5.2	–	–
		8	$R(C(20,15), C(35,20), 1, 1.0)$	0.999462	0.883542	5.96	6.9	6.28%, 1.23%	1.9	8.1	5.81%, 1.24%
		9	$R(C(20,20), C(25, None), 0.99, 0.9966)$	0.999438	0.882269	4.66	6.3	2.76%, 0.58%	1.8	7.9	2.46%, 0.58%
XGBoost	KDD	10	Baseline – $C(450, 3)$	0.999933	0.996294	0.25	196.5	–	13.6	–	–
		11	$R(C(70,5), C(250,3), 0.99, 0.99444)$	0.999934	0.996356	0.32	49.4	0.33%, 0.13%	3.6	11.4	0.12%, 0.10%
		12	$R(C(90,5), C(350,3), 0.99, 0.9988)$	0.999934	0.996357	0.40	65.3	0.70%, 0.24%	4.7	15.1	0.08%, 0.08%
	CCF	13	Baseline – $C(500, 3)$	0.999803	0.877078	0.28	252.4	–	16.4	–	–
		14	$R(C(70,5), C(200,3), 0.99, 0.9977)$	0.999792	0.873624	0.26	61.7	0.82%, 0.15%	3.9	13.0	0.15%, 0.07%
		15	$R(C(90,5), C(300,3), 0.908, 0.98)$	0.999800	0.878426	0.32	77.9	0.09%, 0.05%	4.9	14.7	0.02%, 0.02%
	FC	16	Baseline – $C(2000, 3)$	0.999495	0.891222	1.21	1367.9	–	58.9	–	–
		17	$R(C(70,5), C(300,5), 0.99, 0.995)$	0.999489	0.892526	0.85	79.4	1.94%, 0.50%	3.9	20.5	1.13%, 0.41%
		18	$R(C(70,5), C(500,5), 0.99, 0.99)$	0.999506	0.896179	1.23	83.0	1.49%, 0.48%	4.0	29.9	1.13%, 0.41%
AdaBoost	KDD	19	Baseline – $C(700, 3)$	0.999943	0.996854	0.92	874.6	–	136.6	–	–
		20	$R(C(300,3), C(500,5), 0.64, 0.84)$	0.999955	0.997485	2.48	630.6	99.96%, 1.76%	61.9	165.6	3.67%, 0.47%
		21	$R(C(300,3), C(450,6), 0.669, 0.742)$	0.999947	0.997084	2.69	462.4	59.23%, 1.51%	64.8	149.3	12.53%, 0.86%
	CCF	22	Baseline – $C(1100, 2)$	0.999801	0.876765	0.99	2192.4	–	185.9	–	–
		23	$R(C(200,3), C(450,6), 0.649, 0.649)$	0.999798	0.877588	2.41	716.0	7.60%, 0.12%	39.6	118.4	7.52%, 0.10%
		24	$R(C(450,3), C(350,6), 0.673, 0.855)$	0.999808	0.882403	2.31	3048.6	96.70%, 0.17%	78.7	135.6	14.38%, 0.11%
	FC	25	Baseline – $C(1000, 3)$	0.999449	0.882856	1.44	1333.2	–	235.8	–	–
		26	$R(C(300,4), C(300,6), 0.675, 0.855)$	0.999477	0.892222	2.17	877.5	57.29%, 0.47%	73.2	147.6	4.33%, 0.46%
		27	$R(C(60,3), C(350,5), 0.68, 0.715)$	0.999472	0.889118	3.10	115.9	5.99%, 0.79%	17.8	104.1	3.87%, 0.79%

Table 3: Raspberry Pi 3 - Training-time and classification latency comparison between RADE and the baseline models.

	RF			XGBoost			AdaBoost		
	#	Training time [s]	Classification Latency [μs]	#	Training time [s]	Classification Latency [μs]	#	Training time [s]	Classification Latency [μs]
KDD	1	567	127	10	2068	166	19	11727	1384
	2	63 (9.0×)	26 (4.9×)	11	608 (3.4×)	53 (3.1×)	20	12433 (0.9×)	619 (2.2×)
	3	57 (10.0×)	22 (5.8×)	12	536 (3.9×)	47 (3.6×)	21	8021 (1.5×)	697 (2.0×)
CCF	4	848	89	13	2909	164	22	17524	1889
	5	195 (4.4×)	41 (2.2×)	14	713 (4.1×)	49 (3.3×)	23	24905 (0.7×)	755 (2.5×)
	6	433 (2.0×)	41 (2.2×)	15	892 (3.3×)	45 (3.7×)	24	5681 (3.1×)	425 (4.4×)
FC	7	363	66	16	9519	1831	25	24355	2596
	8	113 (3.2×)	28 (2.3×)	17	601 (15.8×)	68 (26.9×)	26	22971 (1.1×)	762 (3.4×)
	9	116 (3.1×)	28 (2.3×)	18	588 (16.2×)	59 (30.8×)	27	2368 (10.3×)	203 (12.8×)

since AdaBoost DTEM is not memory bound (uses trees with only a few (*i.e.,* stumps) to several terminal nodes).

Training time. For all datasets, the training time of RADE is significantly lower. For example, it is $17.2\times$ faster for XGBoost over FC. These lower times adhere with the smaller size of the coarse-grained models the smaller data fractions that are used for the training of the fine-grained models.

Classification latency. The improvement in the mean classification latency of RADE over the baseline is even more significant than in the case of RF. For example, it is $15.1\times$ faster for XGBoost over FC and $13.24\times$ faster for AdaBoost over FC. The worst-case classification time of RADE is also competitive as compared to the baseline and is even superior (by up to $2.83\times$ faster) for the CCF and FC datasets. Note that the classification latency grows linearly with respect to the number of trees but only logarithmic in the (roughly balanced) tree size (*i.e.,* number of terminal nodes). Therefore, the lower number of trees used by the coarse-grained and fine-grained models of RADE results in faster classification as compared to the baseline.

5.4 Raspberry Pi 3 evaluation

We evaluate RADE over Raspberry Pi 3 B+[8] with Raspbian 9.8 OS (Raspberry Pi 3, 2018). Table 3 compares the training time and classification latency of RADE and baseline models, for the same classification DTEM methods and datasets, as in Table 2. The training time improvement of RADE ranges from $0.7\times$ up to $16.2\times$, and the classification latency improvement ranges from $2\times$ up to $30.8\times$.

6 Summary and Future Work

This paper presents RADE, an efficient DTEM classification framework that augments standard DTEM classifiers to obtain lower model memory size, training time and classification latency, while obtaining competitive and often better anomaly detection than the standard (baseline) models. We also believe that RADE can be extended to support multi-class classification. The straightforward approach is having k fine-grained models for k classes. However, an immediate concern is the scalability of this approach with respect to the number of classes. Thus, better approaches that result in less fine-grained models should be considered in order to maintain the competitive attributes of RADE.

[8] ARM Cortex-A53 with 512 KB shared L2 and 1GB SDRAM.

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