Representation of PE Files using LSTM Networks

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Keywords: Malware Detection, PE File Format, Recurrent Neural Network, Long Short-term Memory.

Abstract: An ever-growing number of malicious attacks on IT infrastructures calls for new and efficient methods of protection. In this paper, we focus on malware detection using the Long Short-Term Memory (LSTM) as a preprocessing tool to increase the classification accuracy of machine learning algorithms. To represent the malicious and benign programs, we used features extracted from files in the PE file format. We created a large dataset on which we performed common feature preparation and feature selection techniques. With the help of various LSTM and Bidirectional LSTM (BLSTM) network architectures, we further transformed the collected features and trained other supervised ML algorithms on both transformed and vanilla datasets. Transformation by deep (4 hidden layers) versions of LSTM and BLSTM networks performed well and decreased the error rate of several state-of-the-art machine learning algorithms significantly. For each machine learning algorithm considered in our experiments, the LSTM-based transformation of the feature space results in decreasing the corresponding error rate by more than 58.60 %, in comparison when the feature space was not transformed using LSTM network.

1 INTRODUCTION

Malware is a software that conducts malicious activities on the infected computer. Cybersecurity professionals across the globe are trying to tackle this unwanted behaviour. Even though they are developing defense systems on a daily basis, cybercriminals process at the same, if not, in a faster manner.

Antivirus programs detect more than 370,000 malicious programs each day (AV-test, 2019), and the number keeps rising. Although Windows remains the most attacked platform, macOS and IoT devices are becoming attractive targets as well. The most popular weapon for cybercriminals on Windows remains Trojan, for instance, Emotet, WannaCry, Mirai and many others (Symantec, 2019).

In May 2017, the world was struck by new ransomware WannaCry. This virus quickly spread all around the world, infecting more than 230,000 computers in 150 countries. Between infected organizations were, e.g. FedEx, O2, or Britain's NHS and the cost of damage was estimated at around 4 billion dollars (Latto, 2020).

In the paper, we focus on static malware detection where features are collected from the PE file format. We are not examining files' working behaviour for multiple reasons. Firstly, extracting API calls from executable files needs to be performed in a sandbox environment to secure the leak of possible malicious activities into our system. However, this is bypassed by the unnatural behaviour of many programs in these surroundings. Secondly, it's time-consuming running large datasets and capturing their activities.

During the last years, the current trend is to used malware detection framework based on machine learning algorithms. Thanks to cloud-based computing which makes the cost of big data computing more affordable, the concept of employing machine learning to malware detection has become more realistic to deploy.

This paper aims to explore whether the LSTM networks can transform features to more convenient feature space, and as a result, improve the classification accuracy. This problem is tackled in two stages. In the first stage, we collect malware and benign files, extract useful information, prepare and select the best features to create our dataset. The second stage consists of training different LSTM network architectures, transforming our dataset using these networks, and evaluating our results with the help of several supervised machine learning (ML) algorithms.

The structure of the paper is as follows. In Section 2, we review related work on malware detection using neural networks, especially recurrent neural nets.

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Section 3 describes fundamental background, such as PE file format and LSTM networks. In Section 4, we describe feature preprocessing and propose feature transformation using LSTM networks. Description of our experimental setup, from the dataset and hardware used to final evaluation using supervised ML algorithms, is placed in Section 5. We conclude our work in Section 6.

2 RELATED WORK

In this part, we review related research in the field of static malware detection. We focused on the papers linked to neural networks, notably recurrent neural networks (RNNs). However, we didn't find much work dealing with the use of LSTM networks as a feature pre-treatment before the classification itself.

In (Lu, 2019), the authors used opcodes (operation code, part of machine language instruction (Barron, 1978)) extracted from a disassembled binary file. From these opcodes, they created a language with the help of word embedding. The language is then processed by the LSTM network to get the prediction. They achieved an AUC-ROC score of 0.99, however, their dataset consisted of only 1,092 samples.

A much larger dataset of 90,000 samples was used in (Zhou, 2018). They used an LSTM network to process API call sequences combined with the convolutional neural network to detect malicious files. While also using static and dynamic features, they managed to achieve an accuracy of 97.3%.

Deep neural networks were also used in (Saxe and Berlin, 2015) with the help of Bayesian statistics. They worked with a large dataset of more than 400 thousand binaries. With fixed FPR at 0.1%, they reported AUC-ROC of 0.99964 with TPR of 95.2%.

The authors of (Hardy et al., 2016) used stacked autoencoders for malware classification and achieved an accuracy of 95.64% on 50,000 samples.

In (Vinayakumar et al., 2018), they trained the stacked LSTM network and achieved an accuracy of 97.5% with an AUC-ROC score of 0.998. That said they focused on android files and collected only 558 APKs (Android application package).

3 BACKGROUND

In this chapter, we explain the necessary background for this paper. The first part deals with the Portable Executable file format, describing the use cases and structure. In the second part, we study the LSTM networks in detail. In the end, we also briefly mention the autoencoder networks.

3.1 Portable Executable

Portable Executable (**PE**) **format** is a file format for Windows operation systems (Windows NT) executables, DLLs (dynamic link libraries) and other programs. Portable in the title denotes the transferability between 32-bit and 64-bit systems. The file format contains all basic information for the OS loader (Kowalczyk, 2018).

The structure of the PE file is strictly set as follows. Starting with MS-DOS stub and header, followed with file, optional, and section headers and finished with program sections as illustrated in Figure 1. The detailed description can be found in (Karl Bridge, 2019).

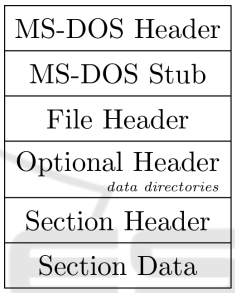


Figure 1: Structure of a PE file.

3.2 LSTM Network

Long short-term memory or shortly **LSTM** network is a subdivision of recurrent neural networks. This network architecture was introduced in (Hochreiter and Schmidhuber, 1997). The improvement lies in replacing a simple node from RNN with a compound unit consisting of *hidden state* or h_t (as with RNNs) and so-called *cell state* or c_t. Further, adding *input node* g_t compiling the input for every time step t and three *gates* controlling the flow of information. Gates are binary vectors, where 1 allows data to pass through, 0 blocks the circulation. Operations with gates are handled by using Hadamard (element-wise) product $\odot$ with another vector (Leskovec et al., 2020).

As mentioned above, the LSTM cell is formed by a group of simple units. The key difference from RNN is the addition of three **gates** which regulate the input/output of the cell.

Note that W_x, W_h and $\vec{b}$ with subscripts in all of the equations below are learned weights matrices and vectors respectively, and f denotes an activation function, e.g. sigmoid. Subscripts are used to distinguish matrices and vectors used in specific equations.

1. **Input Gate.** Determines which information can be allowed inside the unit:

$$i_t = f(W_{x_i} x_t + W_{h_i} h_{t-1} + \vec{b}_i) \quad (1)$$

2. **Forget Gate.** Allows us to discard information from memory we do not longer need:

$$f_t = f(W_{x_f} x_t + W_{h_f} h_{t-1} + \vec{b}_f) \quad (2)$$

3. **Output Gate.** This gate learns what data is paramount at a given moment and enables the unit to focus on it:

$$o_t = f(W_{x_o} x_t + W_{h_o} h_{t-1} + \vec{b}_o) \quad (3)$$

The **input node** takes as an input x_t and previous hidden state:

$$g_t = f(W_{x_g} x_t + W_{h_g} h_{t-1} + \vec{b}_g) \quad (4)$$

As an activation function is typically used *tanh* even though *ReLU* might be easier to train (Lipton et al., 2015).

The **cell state** is calculated as follows:

$$c_t = i_t \odot g_t + f_t \odot c_{t-1} \quad (5)$$

In equation (5), we can see the intuition behind using the input and forget gates. The gates handle how much of the input node and previous cell state we allow into the cell. This formula is the essential improvement to simple RNNs as the forget gate vector applied to the previous cell state is what allows the gradient to safely pass during backpropagation, thus abolishing the problem of *vanishing gradient* (Leskovec et al., 2020).

The **hidden state** is then updated with the content of the current cell state modified with output gate o_t as follows:

$$h_t = f(c_t \odot o_t) \quad (6)$$

We can imagine the hidden state as the short-term memory and cell state as the long-term memory of the LSTM network.

The output $\hat{y}_t$ is then computed as:

$$\hat{y}_t = f(W_{h_y} h_t + \vec{b}_y) \quad (7)$$

To see the detailed illustration of LSTM cell see Figure 2.

Presented LSTM architecture in Figure 2 closely maps the state-of-the-art design from (Zaremba et al., 2014). Note that we dropped the network's parameters, matrices of weights, and vectors of biases to keep it well-arranged.

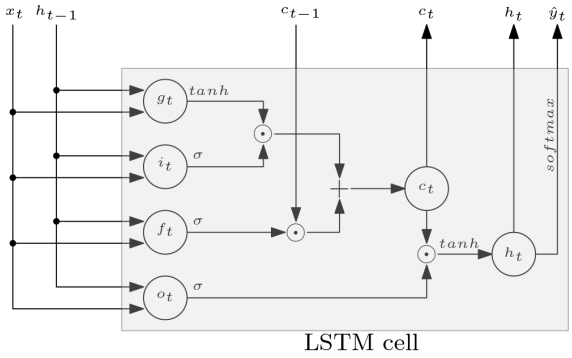


Figure 2: Example of the LSTM architecture.

3.2.1 Bidirectional Long Short-term Memory

The traditional LSTM networks, the same as standard recurrent neural networks and bidirectional recurrent neural networks (BRNNs), are not suitable for some tasks as the hidden and cell states are determined only by prior states. Such tasks include text and speech recognition and many more where the output at a time t depends on the past as well as future inputs or labeling problems where the output is only expected after finishing the whole input sequence (Graves, 2012). **Bidirectional Long Short-Term Memory** or shortly (**BLSTM**) networks try to solve this problem by having connections both from the past and future cells. Input to the BLSTM network is then presented in two rounds, once forwards as with the LSTM network and then in a reversed direction from the back. This architecture was introduced in (Graves and Schmidhuber, 2005).

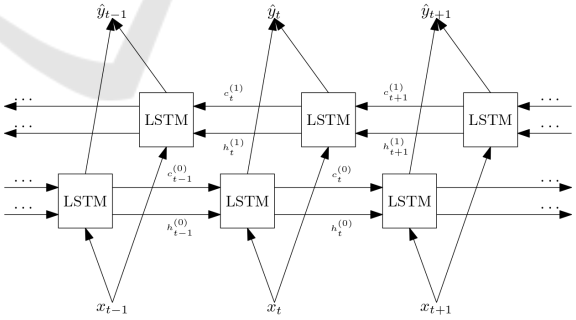


Figure 3: Structure of BLSTM network.

In Figure 3 we can see the structure of BLSTM network, the (0) and (1) in superscripts stand for forwards and backwards directions, respectively. We omitted the detailed representation of LSTM cells to make the illustration simpler.

BLSTM networks can be used to solve similar problems as bidirectional RNNs where we have entire input available beforehand. Training the network in

forward and backward directions helps to gain context from the past and future as well (Brownlee, 2019). In addition, having hidden and cell state enables better storage of information across the timeline even from the distant past or future.

BLSTM networks were found to outperform standard BRNNs in many tasks, e.g. speech recognition. This was proven in the first application of BLSTM networks by Graves et al. for phoneme classification problem (Graves and Schmidhuber, 2005). BLSTMs are not suitable for all tasks, such as where we do not know the final length of the input, and the results are required after each timestamp (*online* tasks).

3.3 Autoencoder

Autoencoder is a type of neural network that can learn a representation of given data by compressing and decompressing the input values. As described in (Chollet, 2016), it consists of two parts, the *encoder* and *decoder*. The encoder is typically a dense feed-forward neural network (other types of neural networks can be used as well) with subsequent layers shrinking in width. The decoder mirrors the structure of the encoder with expanding layers. The autoencoder is then trained with a set of data where input matches the target output. After training, the decoder is detached and the encoder is used as the sole model for prediction. The illustration of the autoencoder setup can be seen in Figure 4.

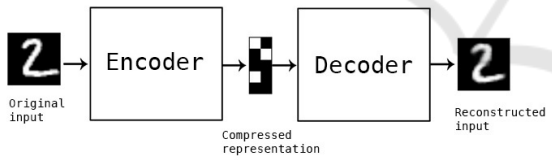


Figure 4: Example of autoencoder for digit compression (Chollet, 2016).

Although the data compressed by autoencoder could be used in image compression, generally autoencoders do not outperform well-known compression algorithms. Since the compression inside autoencoders is not lossless (the output is fuzzy), they are not suitable for practical use of image compression.

Among places where autoencoders found utilization belong dimension reduction and data denoising problems. In dimension reduction, autoencoders are used either as a preprocessing stage in machine learning problems or before data visualization where large data dimension hinders the comprehension of the image. In data denoising, the autoencoder is trained with noisy images as the input and clear pictures being the output. The use of autoencoders is not limited to images, however, they can also be used with audio and other problems affected by noisiness.

4 FEATURE TRANSFORMATIONS USING LSTM NETWORKS

In this section, we present our approach - feature transformation using LSTM networks. We describe feature extraction and preparation, then feature selection along with the central part of this paper, the feature transformation using LSTM networks. Our complete workflow is illustrated in Figure 8 at the end of this section.

4.1 Feature Extraction

For extracting features from PE files, we used Python module `pefile` (Carrera, 2017). This module extracts all PE file attributes into an object from which they can be easily accessed. The structure of the PE files is briefly explained in Section 3.1. We used as many PE attributes as possible and reached the total number of 303 features. Features can be divided into multiple categories based on their origin from the PE file. A summary of all target static features used in our experiments is as follows:

Headers: Data from DOS, NT, File, and Optional headers.

Data Directories: Names and sizes of all data directories. Also adding detailed information from prevalent directories for instance IMPORT, EXPORT, RESOURCE, and DEBUG directories.

Sections: Names, sizes, entropies of all PE sections expressed by their average, min, max, mean and standard deviation. To cooperate with a variable amount of sections in different files, we decided to describe only the first four and last sections individually.

Others: Extra characteristics associated with a file, e.g. byte histogram, printable strings, or version information.

4.2 Feature Preparation

Since not all machine learning models used in our experiments can handle strings and other categorical data, we must such data types encode into numeric values. This strategy is necessary for more than 60 out of 303 columns. We chose to perform common

transformation techniques on the entire dataset as opposed to only using the training set. We believe that by doing so, we can better focus on designing LSTM architectures and our results won't be affected by the capability of other algorithms.

4.2.1 Vectorization

Upfront, we transformed string features into sparse matrix representation using `TfidfVectorizer` from the `scikit-learn` Python library (Pedregosa et al., 2011). This class demands *corpus* (collection of documents) as an input. We also adjusted parameters `stop_words` and `max_df` that influence which words to exclude from further calculations. Among the excluded words are either commonly used words in a given language, words that do not bear any meaning, and words that occur with such high frequencies that they are not statistically interesting for us. To eliminate the massive rise of dimensionality, we set `max_features` parameter according to the feature's cardinality. The transformation itself consists of converting sentences to vectors of token counts. Then they are transformed into tf-idf representation. **Tf-idf** is an abbreviation for the *term frequency times inverse document frequency*. It is a way to express the weight of a single word in the corpus (Maklin, 2019).

Term Frequency is the frequency of a word inside the document. The formula is:

$$\mathrm{tf}(w,d) = \frac{n_{w,d}}{\sum_k n_{k,d}}, \tag{8}$$

where $n_{w,d}$ is the number of times word w appears in a document d and the denominator is the sum of all words found in d.

Inverse Document Frequency is a scale of how much a word is rare across the whole corpus:

$$\mathrm{idf}(w,D) = \log \frac{|D|}{|d \in D : w \in d|} \tag{9}$$

It is a fraction of the total number of documents in corpus D divided by the number of documents containing the specific word.

Tf-idf is then calculated as a multiplication of these two values as follows:

$$\text{tf-idf}(w,d) = \mathrm{tf}(w,d) \cdot \mathrm{idf}(w,D) \tag{10}$$

All of this is done by the aforementioned class `TfidfVectorizer`, and as a result, we get a matrix of tf-idf features that can be used in further computations.

4.2.2 Hashing

For non-string values, we used a technique called **feature hashing**. This approach turns the column of values into a sparse matrix using the value's hash as an index to the matrix. For this task, we used `FeatureHasher` also from the `scikit-learn`. The class takes an optional argument `n_features` which limits the number of columns in the output matrix. We set this argument dynamically according to the size of the feature's value set.

4.3 Feature Selection

Even though we tried to limit the rise of new features, we ended up with 1488 features. To speed up the forthcoming training process, we tried several feature selection techniques to reduce the dimensionality of the dataset.

Before all else, we filled missing values by column's mean and divided data into train and test splits to ensure correct evaluation of the model's performance. For this, we used `train_test_split` from `sklearn.model_selection` with test split taking 20% of the dataset. Afterwards, we transformed features to stretch across a smaller range. For this task, we looked for another class from `sklearn.preprocessing` library and selected `MinMaxScaler`. This scaler turns each feature x to lie between zero and one. The transformation is calculated as:

$$\frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{11}$$

For feature selection, we settled with PCA (Principal Component Analysis) with the number of components determined by testing conducted with the state-of-the-art ML algorithms: AdaBoost, Decision tree, Feed-forward neural network, Random forest, K-nearest neighbours, Support vector machine, Gaussian naive bayes, and Logistic regression. The same ML algorithms were used to evaluate performance of LSTM-based transformation (see Section 5.2). We tested a number of components ranging from 2 to 1400, however increasing benefits were found only until 50 components, after which we did not measure any significant improvements. The results are presented in Figure 5.

Note that while the resulting components are not primarily in the form of sequences, they can still be sequentially processed using the LSTM and achieve solid classification results (see Section 5.3).

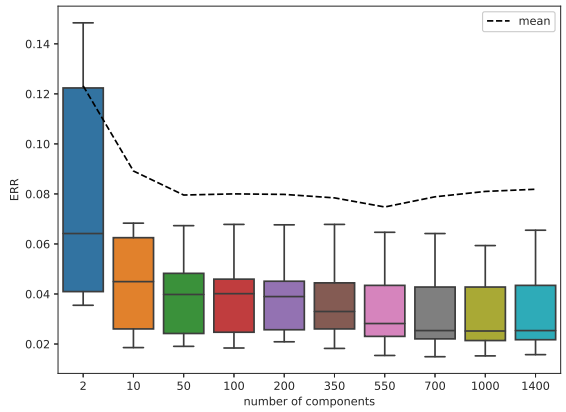


Figure 5: Average error rate (ERR) of ML algorithms across number of components.

4.4 Feature Transformation using LSTM Network

We experimented with various LSTM architectures which we used for feature transformation. All networks were trained only on the train set. After the training process, the train and test set were transformed using the LSTM network.

Our research is not limited to only LSTM networks, however, bidirectional version of LSTM networks (BLSTM) was also included in our experiments. We considered two different types of neural networks: the *Basic version* consisting of one (B)LSTM layer and the *Deep version* with four (B)LSTM layers, each layer containing 50 LSTM units equal to the number of input features. All networks were trained up to 50 epochs with a batch size of 32, Adam optimization, and mean squared error loss function.

4.4.1 Type 1

The first type of LSTM network we experimented is based on autoencoder's architecture. In this case, we worked only with explanatory variables with a network designed to predict the same values which were given on input. The predicted transformation was taken from the penultimate layer's last hidden state. Schema of the Type 1 transformer is illustrated in Figure 6.

4.4.2 Type 2

The second type was similar to the regular use of the LSTM network, where we work with both the explanatory and response variables. For prediction, we used the last hidden state of the penultimate LSTM layer as with Type 1. The last layer was occupied by a single neuron with a sigmoid activation function. Diagram of the Type 2 transformer is presented in Figure 7.

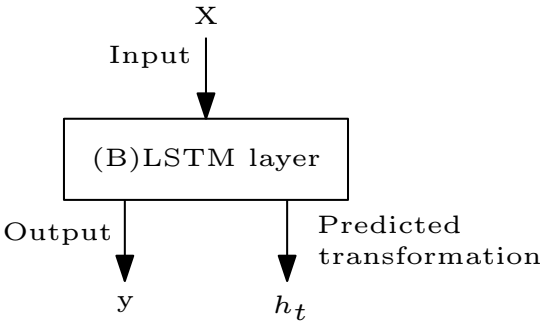


Figure 6: Schema of Basic version Type 1 transformer.

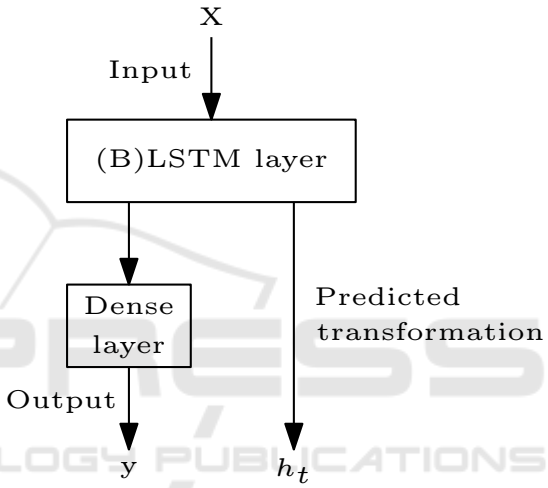


Figure 7: Schema of Basic version Type 2 transformer.

4.4.3 Description of All Transformed Datasets

The following is a description of the datasets used in testing. Recall that "Basic" and "Deep" in the description below denote one layer and four layers of the deep network, respectively:

BLSTM_AE_basic Transformed by Basic version of BLSTM Type 1 (autoencoder) network.

BLSTM_AE_deep Transformed by Deep version of BLSTM Type 1 (autoencoder) network.

BLSTM_basic Transformed by Basic version of BLSTM Type 2 network.

BLSTM_deep Transformed by Deep version of BLSTM Type 2 network.

LSTM_AE_basic Transformed by Basic version of LSTM Type 1 (autoencoder) network.

LSTM_AE_deep Transformed by Deep version of LSTM Type 1 (autoencoder) network.

LSTM_basic Transformed by Basic version of LSTM Type 2 network.

LSTM_deep Transformed by Deep version of LSTM Type 2 network.

VANILLA Control dataset, no transformations made.

4.5 Evaluation using Supervised ML Algorithms

The final part of the experiment workflow consists of evaluation of the aforementioned transformations. We tested several supervised ML algorithms and compared their performance on vanilla and transformed datasets. Detailed description of this part can be found in Section 5.2. Figure 8 overviews the experiment pipeline.

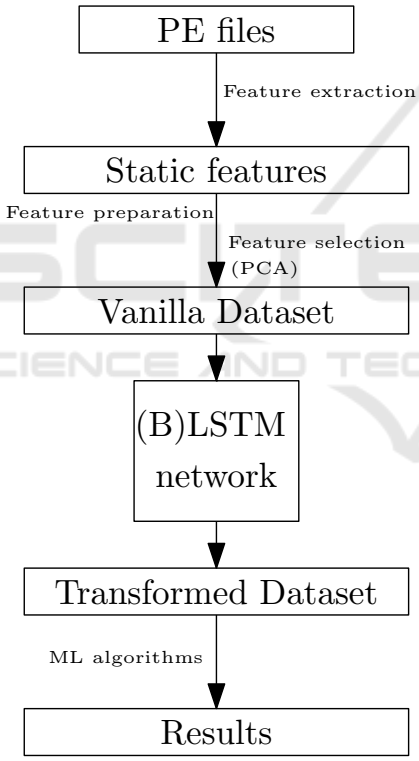


Figure 8: Experiment pipeline.

5 EXPERIMENTS

In this section, we firstly describe the dataset used in our experiments. Then we specify our experimental setup in detail and evaluation methods, and in the end, we present our results.

5.1 Dataset

We gathered a dataset of 30,154 samples which are evenly distributed between malware and benign files. For amassing benign files, we searched disks on university computers and the malware files were obtained from an online repository https://virusshare.com which we thanks for the access.

5.2 Experimental Setup and Evaluation Methods

The performance of LSTM pre-treatment was evaluated by the following supervised ML algorithms. Among the ML algorithms we used were Support vector classification (SVC) with kernel *rbf*, deep Feed-forward network (FNN) with 8 hidden layers (128-128-64-64-32-32-16-16 neurons per layer) all with *ReLU* activation function, trained up to 200 epochs with Adam optimization and binary cross-entropy loss function. Further, we tested Decision tree, Random forest, AdaBoost, K-nearest neighbours (k=5), Gaussian naive bayes, and Logistic regression. The hyperparameters which we did not mention were left to default settings as set by authors of the `scikit-learn` library (Pedregosa et al., 2011) except for the FNN which was modeled with the help of the Python deep learning library `Keras` (Chollet et al., 2015).

Our implementation was executed on a single computer platform having two processors (Intel Xeon Gold 6136, 3.0GHz, 12 cores each), with 32 GB of RAM running the Ubuntu server 18.04 LTS operating system.

5.2.1 Metrics

In this section, we present the metrics we used to measure the performance of our proposed classification models. For evaluation purposes, the following classical quantities are employed:

True Positive (TP) represents the number of malicious samples classified as malware.

True Negative (TN) represents the number of benign samples classified as benign.

False Positive (FP) represents the number of benign samples classified as malware

False Negative (FN) represents the number of malicious samples classified as benign.

The performance of our classifiers on the test set is measured using the following standard metrics:

Accuracy (*ACC*) Proportion of correctly classified samples out of all predictions:

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

Error rate (*ERR*) The inverse of accuracy:

$$ERR = 1 - ACC \quad (13)$$

Sensitivity (*TPR, Recall*) How many samples from the positive class were predicted correctly:

$$TPR = \frac{TP}{TP+FN} \quad (14)$$

Fall-out (*FPR*) Probability of predicting samples from the negative class as positives:

$$FPR = \frac{FP}{FP+TN} \quad (15)$$

5.3 Results

In order to expose any biases in the data, we tested the ML algorithms with 5-fold cross-validation using `cross_validate` from `scikit-learn` library.

We found that the results did not only vary between different network architectures but also among particular ML algorithms. These observations are presented in the heatmap in Figure 9. These results indicate that Type 1 based on autoencoder design does not seem to improve the performance whatsoever. However, Type 2, especially deep versions of LSTM and BLSTM networks, seem to enhance the performance of many algorithms significantly.

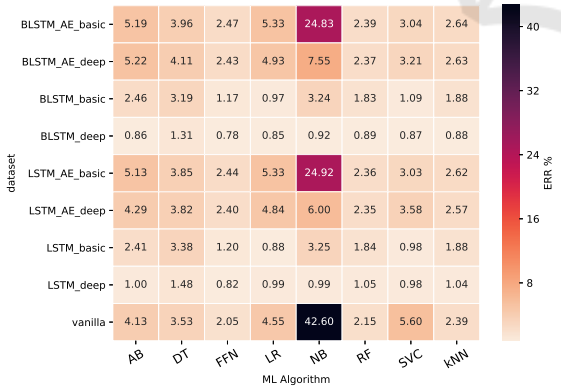


Figure 9: Heatmap comparing the ERR of ML algorithms with respect to different transformer architectures.

Tables 1, 2 and 3 present the improvements made by pre-treatment with LSTM and BLSTM networks for different ML algorithms used for evaluation. Note that the performance of Logistic regression, Naive Bayes, SVC, or AdaBoost algorithms increased the most significantly.

Table 1: Baseline results of ML algorithms on unedited (vanilla) dataset.

ML Algorithm	ACC	TPR	FPR	ROC-AUC
AdaBoost	95.87 ± 0.39	95.49 ± 0.55	3.75 ± 0.46	95.87 ± 0.39
DecisionTree	96.47 ± 0.20	96.37 ± 0.25	3.44 ± 0.40	96.47 ± 0.20
Feed-ForwardNetwork	97.95 ± 0.12	97.75 ± 0.36	1.86 ± 0.23	97.95 ± 0.12
LogisticRegression	95.45 ± 0.38	94.62 ± 0.38	3.73 ± 0.45	95.45 ± 0.38
NaiveBayesGaussian	57.40 ± 16.01	16.63 ± 36.13	1.84 ± 4.11	57.40 ± 16.01
RandomForest	97.85 ± 0.20	97.52 ± 0.24	1.82 ± 0.19	97.85 ± 0.20
SVC(kernel=rbf)	94.40 ± 1.74	93.49 ± 1.74	4.69 ± 1.81	94.40 ± 1.74
kNN(k=5)	97.61 ± 0.21	97.17 ± 0.28	1.94 ± 0.16	97.61 ± 0.21

Table 2: Results of ML algorithms on dataset transformed by deep LSTM network.

ML Algorithm	ACC	TPR	FPR	ROC-AUC
AdaBoost	99.00 ± 0.71	98.76 ± 0.78	0.76 ± 0.66	99.00 ± 0.71
DecisionTree	98.52 ± 0.55	98.43 ± 0.60	1.40 ± 0.50	98.52 ± 0.55
Feed-ForwardNetwork	99.18 ± 0.77	99.10 ± 0.64	0.75 ± 0.90	99.18 ± 0.77
LogisticRegression	99.01 ± 0.72	98.89 ± 0.78	0.87 ± 0.67	99.01 ± 0.72
NaiveBayesGaussian	99.01 ± 0.67	98.70 ± 0.58	0.69 ± 0.78	99.01 ± 0.67
RandomForest	98.95 ± 0.77	98.85 ± 0.77	0.95 ± 0.78	98.95 ± 0.77
SVC(kernel=rbf)	99.02 ± 0.72	98.73 ± 0.74	0.69 ± 0.70	99.02 ± 0.72
kNN(k=5)	98.96 ± 0.75	98.82 ± 0.80	0.91 ± 0.71	98.96 ± 0.75

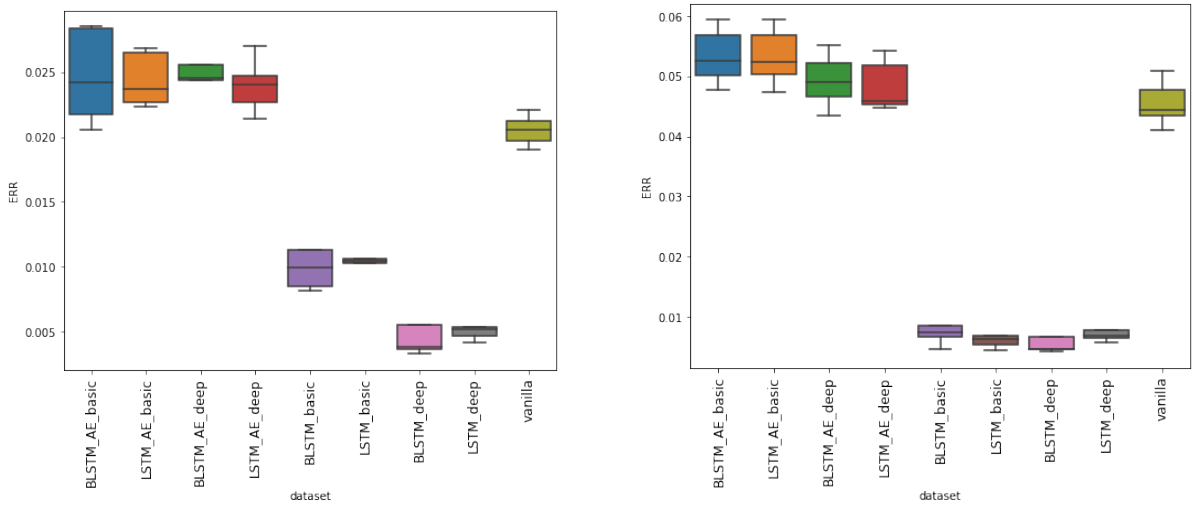
The performance of the two most successful classifiers evaluated on all transformed datasets considered in our experiments, Feed-forward neural network, and Logistic regression, is presented in Figure 10.

To emphasize our results, we express the performance of the ML algorithms in terms of error rate (in [%]). In Table 4, we overview the error rates (ERR) of ML algorithms evaluated on the original and transformed dataset by deep BLSTM network.

6 CONCLUSIONS

We collected a large number of PE binaries from available resources. From these binaries, we extracted as many features as possible, which we later scale down by the feature selection algorithm PCA in order to reduce the dimension of our dataset. After that, we conducted extensive testing with various (B)LSTM network architectures used to transform the selected features. On these transformed datasets, we ran a cross-validation benchmark using multiple supervised ML algorithms to see whether the feature transformation based on (B)LSTM networks can increase the performance of the ML algorithms in comparison to the performance to the accuracy on the vanilla dataset.

We have found that the feature transformation by (B)LSTM nets was hugely successful, decreasing error rate from 58.6% to 97.84% depending on the ML algorithm used. These gains were achieved by so-called Type 2 architecture which was similar to the standard use of recurrent neural networks for classification problems. In contrast, the Type 1 design based on autoencoder structure didn't prove to en-



(a) Feed-forward neural network.

(b) Logistic regression.

Figure 10: Boxplots showing the performance of the two most successfull classifiers evaluated on multiple datasets.

Table 3: Results of ML algorithms on dataset transformed by deep BLSTM network.

ML Algorithm	ACC	TPR	FPR	ROC-AUC
AdaBoost	99.14 ± 0.77	99.06 ± 0.81	0.78 ± 0.80	99.14 ± 0.77
DecisionTree	98.69 ± 0.71	98.67 ± 0.79	1.30 ± 0.65	98.69 ± 0.71
Feed-ForwardNetwork	99.22 ± 0.84	99.12 ± 0.87	0.67 ± 0.83	99.22 ± 0.84
LogisticRegression	99.15 ± 0.78	99.07 ± 0.81	0.78 ± 0.79	99.15 ± 0.78
NaiveBayesGaussian	99.08 ± 0.78	98.65 ± 0.82	0.48 ± 0.77	99.08 ± 0.78
RandomForest	99.11 ± 0.74	99.01 ± 0.80	0.78 ± 0.72	99.11 ± 0.74
SVC(kernel=rbf)	99.13 ± 0.82	98.94 ± 0.87	0.67 ± 0.79	99.13 ± 0.82
kNN(k=5)	99.12 ± 0.82	99.02 ± 0.87	0.78 ± 0.79	99.12 ± 0.82

Table 4: Comparison of the results achieved from the ML algorithms evaluated on the vanilla (non-transformed) dataset and the transformed dataset by deep BLSTM network.

ML Algorithm	ERR (no LSTM)	ERR (with LSTM)	ERR decreased by
AdaBoost	4.13	0.86	79.18
DecisionTree	3.53	1.31	62.89
Feed-ForwardNetwork	2.05	0.78	61.95
LogisticRegression	4.55	0.85	81.32
NaiveBayesGaussian	42.60	0.92	97.84
RandomForest	2.15	0.89	58.60
SVC(kernel=rbf)	5.60	0.87	84.46
kNN(k=5)	2.39	0.88	63.18

hance performance. The transformation by Type 2 deep transformers brought all tested ML algorithms to a similar level. The smaller performance increments were observed among the ML algorithms which already performed well on the non-transformed dataset.

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