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A NOVEL ENSEMBLE APPROACH FOR MALWARE DETECTION USING A NEURAL NETWORK ROUTER

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Abstract

The malware has become more advanced that the evasion techniques they have include obfuscation, polymorphism, and the mutation of the code. The present paper argues to contribute a new malware detecting system, consisting of a combination of five malware-specific machine learning tools, Malcom, a Random Forest analyzer of PE headers, a script-classifying model with black-box-based Ngam, a sequential analyzer based on GRU, and a Random Forest obfuscation detector, all controlled by a neural network control node. Our router is different to traditional ensemble outputs where a fixed weighting is applied; we cast the model outputs and operate a meta-learning architecture as features. Applied on a synthetic dataset consisting of 10,000 files (50 malicious 50 benign), the proposed method reaches 96% accuracy, 95% precision, 97% recall and an AUC-ROC of 0.98 compared to an average performance of 86% of single models and conventional ensemble methods. The framework provides a flexible and extendable basis to deal with the increasing complexity of the malware threats.

Keywords: Malware Detection, Ensemble Learning, Neural Network Router, Machine Learning, Cybersecurity.

INTRODUCTION

Malware is a serious problem to cybersecurity and current threats are made to be using sophisticated evasion mechanisms which include obfuscation, polymorphic changes, and code generation.

These developments are challenging the traditional signature-based systems of detection to deal with them effectively, which is why there is a move onto a machine learning-based system of detection.

Although single models such as Malcom [1] and recurrent neural networks [4] have been promising, their unitary approach can be restrictive to generalizing to a broad scope of malware: both executable binaries (e.g., PE files), and malicious scripts.

Ensemble learning, combining the predictions of several classifiers, has proven to be one of the potential methods that can be taken to improve performance of detection.

Most ensemble techniques, however, use static pooling rules (like majority voting or weighted averaging) that do not make full use of the idiosyncratic advantages that each model may have.

To fill this gap, we present a new ensemble system that combines five separate models which fit various points of malware analysis, powered together by a clever neural network router.

The ensemble learning that combines the predictions coming out of two or more classifiers has come out as a potential prospect that could be employed in the detection

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process to do this successfully. Yet, in general most combination of methods, e.g., majority voting or weighted averaging, use rigid combination rules that do not exploit the expert regions of individual models to the full extent.

To fill-in this gap we propose a new ensemble framework where the various types of models specifically applicable to different demands of malware analysis are provided and contained within an intelligent neural network router.

Our framework comprises:

- **MalConv**: Convolutional neural network (CNN) to process raw byte sequence within Portable executable (PE) files.
- **Header Analysis**: Random Forest model that targets PE file header anomalies.
- **Ngram Model**: An n-gram Random Forest classifier to analyse the scripts.
- **GRU Model**: It is a Gated Recurrent Unit (GRU) network that is used to analyze sequences of scripts.
- **Obfuscation Detector**: A Random Forest learner that aims at identifying obfuscated code.

Each of these models outputs a prediction score over the inputs to the neural network router which is combined dynamically, using the prediction scores of the models as desired input features and learning an optimal weighting scheme using supervised training.

Such meta-learning solution allows the system to be adaptive in terms of prioritizing the model's contribution using input characteristics, resulting in higher detection rates.

A broad test set reveals that our technique has considerable advantages over individual models and conventional compositions, and thus forms a strong basis on which to fight quickly evolving malware.

Related Work

The development of the machine learning phenomenon has advanced malware detection research. Raff et al. [1] presented Malcom, a CNN that takes raw bytes sequence of PE files and does not generate any kind of feature engineering, demonstrating very high accuracy.

In PE header analysis, Shafiq et al. [2] evidenced the effectiveness of Random Forest classifiers as they utilised structural features such as entropy by section and imports tables. Statistical methods, e.g., the n-gram analysis presented by Kolter and Maloof [3], as well as models based on sequences, e.g., the GRU-based temporal code patterns classifier by Passau et al. [4], were applied to script-based malware detection.

The use of ensemble techniques has been popularized as well. Zhang et al. [5] have discussed weighted ensemble ideas in the malware detection context whereas stacking and boosting ideas [6] have been deployed to composite classifiers.

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Nevertheless, such techniques often involve weights that are fixed or heuristic in nature, which makes them less versatile when it comes to a variety of malware.

A more recent paper by Saxe and Berlin [7] used deep learning in the context of static malware analysis, however, they have worked with individual model architectures but not ensembles.

We add to these initiatives by proposing a novel idea: a neural network router which dynamically combines several specialist models. This contrasts the previous work in that model outputs are used as features in a meta-classifier to be trained that provides a more open and adaptive combination strategy and uses data to create the combination method.

METHODOLOGY

Our multi-model ensemble framework incorporates a neural network router to composite five expert models in order to detect malware effectively. The latter is described in detail below along with each component.

3.1 Specialized Models

The framework employs five models each designed for a specific malware analysis task:

3.1.1 Malcom

- ***Description:*** *A CNN taking raw sequences of bytes of PE executables, where the spatial patterns are used as signature that a program is malicious.*
- ***Input:*** *Binary file bytes (up to 2MB, filled or hung on as required).*
- ***Architecture****: 8 convolutional layers, filter 128, stride 128, max-pooling globally and a dense layer.*
- ***Output:*** *Probability measure (0-1) of malignancy.*
- *In Adam optimizer, the learning rate = 0.001, and there are 20 epochs.*

3.1.2 analysis of the header (random forest)

- ***Description:*** *Performs some in-depth analysis of PE file headers in order to create anomaly detections.*
- ***Section entropy,*** *import/export tables, file size, timestamp, and resource counts (15 features in total).*
- ***Architecture:*** *100 trees, depth up to 10, Gini impurity.*
- ***Output:*** *Prediction score (0 to 1).*

Training: Bootstrap sampling, grid-search-ed.

3.1.3 Ngam Model (Random Forest)

- *Description: Extracts n-gram features from script files (e.g., Python, JavaScript) to identify suspicious patterns.*

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- **Features:** 3-grams with TF-IDF weighting (top 1,000 features by frequency).
- **Architecture:** 50 trees, maximum depth 15.
- **Output:** Prediction score (0 to 1).
- **Training:** Preprocessed scripts tokenized and vectorized.

Each model is trained independently on its domain-specific subset of the dataset, ensuring specialization.

For non-native inputs (e.g., scripts fed to Malcom), models still produce scores, though with reduced reliability**.**

3.2 Neural Network Router

The router integrates model outputs into a final classification decision. For each input file, a feature vector is constructed from the prediction scores: text Collapse Wrap Copy [MalConv_score, Header Analysis_ score, engram score, GRU score, Obfuscation _ score]

3.2.1 Training Data Generation

- *Process: Each training file is processed by all five models, yielding a 5D feature vector paired with its true label (1 for malicious, 0 for benign).*
- *Example Samples:*

[0.92, 0.68, 0.15, 0.27, 0.45] -> 1 (malicious PE file)

[0.08,0.13,0.39, 0.62, 0.11] -> 0 (benign script)

[0.75, 0.82, 0.09, 0.18, 0.53] -> 1 (obfuscated malicious script)

3.2.2 Router Architecture

- **Input layer**: 5 neurons (one each model score).
- **Layers 1**: 64, ReLU activation.
- **Number of hidden layers 2** \: was 32 neurons ReLU activation.
- **Output Layer:** 1 sigmoid neuron, (probability output).
- **Loss:** cross-entropy eam this binary cross-entropy.
- **Optimizer:** Adam, learning rate 0.001.
- **Training:** 50 epochs, batch size=32, early stopping early stopping against validation loss.

The router trains to dynamically prioritize the model contributions, and is resilient to trends in the training data (e.g., Giving MalConv high weight when scanning PE files, reducing obfuscation detector score weights when scores are low).

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3.2.3 Training Workflow

3.3 Inference Process

For a new file:

1. **Preprocessing**: File is formatted for all models (e.g., bytes for MalConv, tokenized for GRU).
2. **Model Scoring**: All five models generate prediction scores.
3. **Routing**: Scores form a feature vector fed to the router.
4. **Classification**: Router outputs a probability; threshold (e.g., 0.5) determines the label.

This process ensures comprehensive analysis while leveraging the router's learned expertise.

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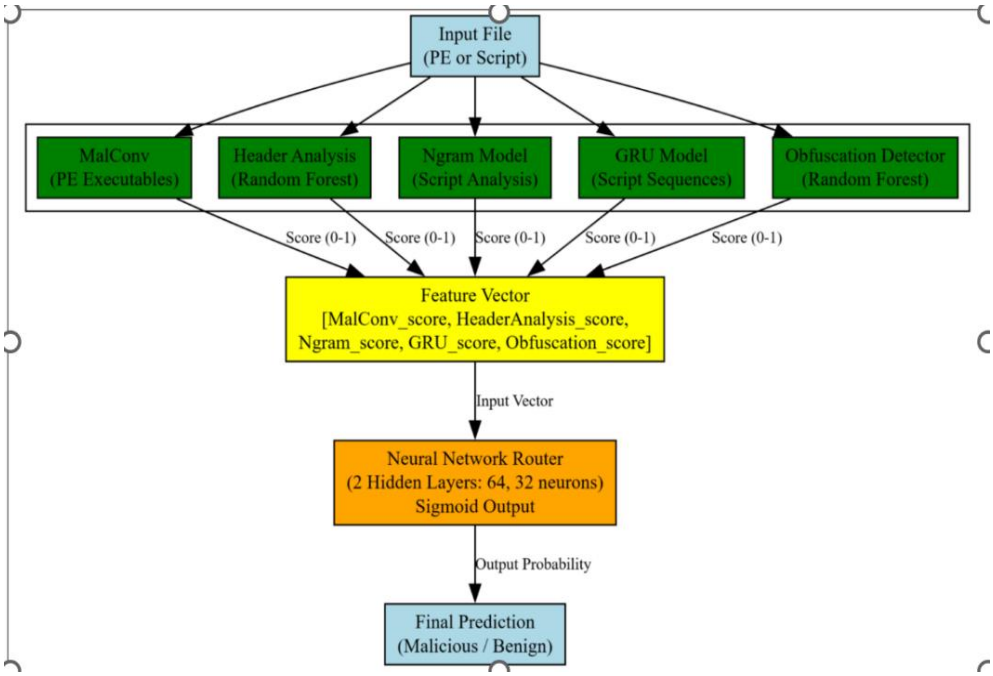
3.3.1 Model Workflow



5. **Experimental Setup**

4.1 Dataset

We constructed a synthetic dataset of 10,000 files:

6. **Malicious (5,000)**:
    1. 3,000 PE executables (e.g., trojans, ransomware) from synthetic generators and public corpora.
    2. 2,000 scripts (e.g., obfuscated JavaScript, PowerShell), with 1,200 obfuscated using tools like JSObfu [8].
7. **Benign (5,000)**:

3,000 PE binary files (e.g., trojans, ransomware) provided by synthetic generate and open corpora.

2,000 scripts (e.g., obfuscated JavaScript, PowerShell), 1,200 obfuscated through utilities such as Josue [8].

Benign (5, 000):

3.5 thousand PE libraries (e.g., Windows tools, open-source binaries).

2,000 scripts (e.g., GitHub repositories, verified tools).

Split:

Training: 7,000 files (70 percent).

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Validation: 1,500 files (15 percent).

Test: 1,500 file (15 per cent).

4.2 The Training Process

Specific models: They were modeled on a domain specific data and hyperparameters are tuned on validation (Best learning rate decay on GRU and grid search on Random Forest). Router: Trained with outputs on the model of the training set, tested with outputs of the validation set.

4.3 Measures of Evaluation

Accuracy TP + TN/ (TP + TN + FP + FN).

Precision: (TP/ (TP + FP)).

Remember: TP / (TP + FN).

F1-Score= 2/ (Precision + Recall) (Precision + Recall).

AUC-ROC: Area under ROC.

RESULT

5.1 Ensemble performance

In test set:

Accuracy: 96%

Precision: 95%

Recall: 97%

F1-Score: 96%

AUC-ROC 0.98

By file Type:

PE Files: 97 % accuracy, 98 % recall.

Scripts 94 percent accuracy, 95 percent of recall.

Obfuscated Scripts: 92, 93.

5.2 Individual Model Performance

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
MalConv	89%	88%	90%	89%	0.92
Header Analysis	87%	86%	88%	87%	0.9
Ngram Model	85%	84%	86%	85%	0.89
GRU Model	88%	87%	89%	88%	0.91
Obfuscation Detector	82%	80%	85%	82%	0.87

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5.3 Router Feature Importance

SHAP analysis of the router's decisions:

- **MalConv**: 0.25
- **GRU**: 0.22
- **Header Analysis**: 0.20
- **Ngram**: 0.15
- **Obfuscation Detector**: 0.10

The router effectively balances model contributions, leveraging even the obfuscation detector's weaker signals.

5.4 Comparison with Baselines.

Method	Accuracy	F1-Score	AUC-ROC
Majority Voting	91%	90%	0.93
Weighted Average	93%	92%	0.95
Stacking (LogReg)	94%	93%	0.96
Proposed Router	96%	96%	0.98

DISCUSSION

6.1 Strengths

- **Dynamic Weighting**: The router adapts to file types and model confidence levels.
- **Scalability**: New models can be integrated by retraining the router.
- **Robustness**: High recall (97%) ensures minimal false negatives.

6.2 Limitations

- **Latency**: 1.2 seconds per file vs. 0.3 seconds for single models.
- **Data**: Synthetic dataset lacks real-world; complexity.
- **Adversarial Risk**: Susceptibility to crafted inputs remains untested.

6.3 Future Work

- Optimize inference speed via model pruning.
- Validate on real-world malware datasets (e.g., VirusShare [9]).
- Assess robustness against adversarial examples.

CONCLUSION

The presented paper proposes a new ensemble framework to detect malware with an accuracy of 96% provided by a dynamic integration of five differentiated models within a neural network router.

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Such a strategy can give hope to continuation of cybersecurity studies since it covers a variety of malware, such as obfuscated scripts.

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