

Contents

| | | |
|----------|--|-----------|
| 1 | Introduction | 1 |
| 1.1 | Introduction | 1 |
| 1.2 | Malware and Its Types | 3 |
| 1.3 | Stages of a Malware Attack | 3 |
| 1.4 | Defense Approaches | 5 |
| 1.4.1 | Signature-based Detection | 5 |
| 1.4.2 | Anomaly-based Detection | 6 |
| 1.5 | Motivation | 7 |
| 1.6 | Objectives | 8 |
| 1.7 | Contributions | 10 |
| 1.8 | Organization of Thesis | 11 |
| 2 | Background | 13 |
| 2.1 | Networks | 13 |
| 2.2 | Network Components and Protocols | 14 |
| 2.3 | Network Architectures and Topologies | 14 |
| 2.4 | Network Devices | 16 |
| 2.5 | Operating Systems | 17 |

| | | |
|--------|---|----|
| 2.6 | Security Vulnerabilities | 18 |
| 2.7 | Malware Authors | 19 |
| 2.8 | Malware Attack Categories | 19 |
| 2.8.1 | Propagation Methods | 19 |
| 2.8.2 | Evasion Methods | 21 |
| 2.8.3 | Targeted Platform | 22 |
| 2.8.4 | Infected Objects | 23 |
| 2.9 | Sandboxes and Its Types | 24 |
| 2.10 | Honeynet System | 25 |
| 2.10.1 | Honeypots | 25 |
| 2.10.2 | Honeynet Architecture | 25 |
| 2.10.3 | Deployment Strategies | 26 |
| 2.11 | Malware Analysis | 26 |
| 2.11.1 | Static Analysis | 26 |
| 2.11.2 | Dynamic Analysis | 27 |
| 2.11.3 | Automated Analysis | 28 |
| 2.11.4 | Manual Code Reversing | 28 |
| 2.11.5 | Recent advances in Malware Analysis | 29 |
| 2.12 | Representation of Malware Data | 30 |
| 2.13 | Malware as a Service (MaaS) Model | 31 |
| 2.14 | Feature Selection | 33 |
| 2.14.1 | Filter Approach | 33 |
| 2.14.2 | Wrapper Approach | 34 |

| | | |
|----------|--|-----------|
| 2.14.3 | Embedded Approach | 34 |
| 2.14.4 | Hybrid Approach | 34 |
| 2.15 | Machine Learning | 34 |
| 2.15.1 | Supervised Learning | 35 |
| 2.15.2 | Unsupervised Learning | 35 |
| 2.15.3 | Reinforcement Learning | 35 |
| 2.15.4 | Ensemble Learning | 36 |
| 2.16 | Deep Learning | 36 |
| 2.16.1 | Artificial Neural Networks | 36 |
| 2.16.2 | Convolutional Neural Network (CNN) | 37 |
| 2.16.3 | Generative Adversarial Networks | 39 |
| 2.16.4 | Graph Neural Networks | 39 |
| 2.17 | Evaluation Metrics | 40 |
| 2.17.1 | Accuracy | 40 |
| 2.17.2 | Precision | 40 |
| 2.17.3 | Recall | 41 |
| 2.17.4 | F1 Score | 41 |
| 2.17.5 | AUC-ROC | 41 |
| 2.18 | Discussion | 42 |
| 3 | Malware Dataset Generation and Evaluation | 43 |
| 3.1 | Introduction | 43 |
| 3.1.1 | Importance of Malware Datasets and Their Desired Characteristics | 44 |

| | | |
|----------|--|-----------|
| 3.1.2 | Motivation | 46 |
| 3.1.3 | Contributions | 46 |
| 3.2 | Background | 47 |
| 3.2.1 | Representation of Malware and Their behavior | 47 |
| 3.2.2 | Benchmark Datasets | 49 |
| 3.3 | TUMALWD: Windows Malware Dataset Creation Framework | 51 |
| 3.3.1 | Phase 1: Data Collection and Storage | 51 |
| 3.3.2 | Phase 2: Data Analysis | 53 |
| 3.3.3 | Phase 3: Feature Engineering | 53 |
| 3.3.4 | TUMALWD: The Dataset and Its Characteristics | 55 |
| 3.4 | TUANDROMD: The Proposed Android Malware Dataset Creation Framework | 58 |
| 3.4.1 | Phase 1: Data Collection and Storage | 58 |
| 3.4.2 | Phase 2: Data Analysis | 59 |
| 3.4.3 | Phase 3: Feature Engineering | 59 |
| 3.4.4 | TUANDROMD: The proposed dataset and its characteristics | 59 |
| 3.5 | Performance Evaluation and Validation | 61 |
| 3.6 | Additional Malware Feature Datasets | 62 |
| 3.6.1 | Image-Based Malware Feature Dataset | 62 |
| 3.6.2 | Function Call Graph (FCG) Dataset | 62 |
| 3.7 | Discussion | 63 |
| 4 | An Enhanced Feature Selection Method for Imprecise Data | 64 |
| 4.1 | Introduction | 64 |

| | | |
|----------|---|-----------|
| 4.1.1 | Motivation | 65 |
| 4.1.2 | Contribution | 66 |
| 4.2 | Background | 66 |
| 4.2.1 | Filter Methods | 67 |
| 4.2.2 | Wrapper Methods | 67 |
| 4.2.3 | Embedded Methods | 67 |
| 4.2.4 | Hybrid Methods | 68 |
| 4.2.5 | Supervised Method | 69 |
| 4.2.6 | Unsupervised Method | 69 |
| 4.2.7 | Semi-supervised Method | 70 |
| 4.3 | Problem Statement | 71 |
| 4.4 | Proposed Method: FSR | 71 |
| 4.4.1 | Rough Set | 71 |
| 4.4.2 | Significance of FSR | 79 |
| 4.5 | Performance Analysis | 79 |
| 4.5.1 | Datasets and Preprocessing | 80 |
| 4.5.2 | Result Analysis and Performance Comparison | 80 |
| 4.6 | Discussion | 87 |
| 5 | A Cost-Effective Method for Ransomware Detection | 88 |
| 5.1 | Introduction | 88 |
| 5.1.1 | Motivation | 89 |
| 5.1.2 | Contribution | 89 |
| 5.2 | Background | 90 |

| | | |
|----------|--|------------|
| 5.3 | Problem Statement | 95 |
| 5.4 | Proposed Framework | 95 |
| 5.4.1 | Data Collection | 96 |
| 5.4.2 | Data Preprocessing | 97 |
| 5.4.3 | Ensemble Feature Selection | 97 |
| 5.4.4 | Classification of Ransomware family and Its Variants | 102 |
| 5.5 | Results | 103 |
| 5.5.1 | Computation of weights for classifiers using NSGA-II | 103 |
| 5.5.2 | Weighted Majority Based Combination Function | 104 |
| 5.5.3 | Classification of Ransomware Variants | 105 |
| 5.5.4 | Classification of Ransomware Family | 105 |
| 5.5.5 | Result analysis and Performance comparison | 105 |
| 5.6 | Discussion | 109 |
| 6 | An Ensemble Approach for Effective Malware Detection | 110 |
| 6.1 | Introduction | 110 |
| 6.1.1 | Motivation | 111 |
| 6.1.2 | Contribution | 112 |
| 6.2 | Background | 112 |
| 6.2.1 | Feature selection | 112 |
| 6.2.2 | Ensemble Feature Selection | 113 |
| 6.2.3 | Markov Chain | 114 |
| 6.3 | Problem Statement | 115 |
| 6.4 | Proposed Method | 115 |

| | | |
|----------|---|------------|
| 6.4.1 | Extraction of indicator of compromises | 116 |
| 6.4.2 | Selection of key indicators | 116 |
| 6.4.3 | Complexity Analysis | 119 |
| 6.4.4 | Optimal Features | 119 |
| 6.5 | Performance Analysis | 121 |
| 6.5.1 | Datasets and preprocessing | 121 |
| 6.5.2 | Classification Performance Analysis and Comparative Eval- uation | 121 |
| 6.6 | Discussion | 125 |
| 7 | Parallel k-Nearest Neighbors for Enhanced Malware Detection | 126 |
| 7.1 | Introduction | 126 |
| 7.1.1 | Motivation | 127 |
| 7.1.2 | Contribution | 128 |
| 7.2 | Background | 129 |
| 7.2.1 | Introduction to K-Nearest Neighbors (K-NN) | 129 |
| 7.2.2 | Proximity Measures | 129 |
| 7.2.3 | Introduction to CUDA | 130 |
| 7.3 | Problem Statement | 132 |
| 7.4 | Proposed Work | 133 |
| 7.4.1 | Distance Measures | 133 |
| 7.4.2 | Sequential KNN algorithm | 136 |
| 7.4.3 | TUKNN Algorithm | 136 |
| 7.4.4 | Complexity Analysis | 137 |

| | | |
|----------|--|------------|
| 7.5 | Implementation and results | 137 |
| 7.5.1 | Dataset Used | 138 |
| 7.5.2 | Results and Observation | 139 |
| 7.6 | Discussion | 166 |
| 8 | A Deep Learning Based Malware Detection Method | 168 |
| 8.1 | Introduction | 168 |
| 8.1.1 | Motivation | 169 |
| 8.1.2 | Contribution | 170 |
| 8.2 | Background | 170 |
| 8.2.1 | Neural Networks | 170 |
| 8.2.2 | Convolutional Neural Networks (CNNs) | 172 |
| 8.3 | Problem statement | 174 |
| 8.4 | The Proposed Method | 175 |
| 8.4.1 | Feature Data Generation | 175 |
| 8.4.2 | Data Preprocessing | 178 |
| 8.4.3 | Selection of CNN architectures | 179 |
| 8.4.4 | Transfer Learning and Fine-tuning Approaches | 179 |
| 8.5 | Experimental Results | 181 |
| 8.5.1 | Datasets | 181 |
| 8.5.2 | Results | 182 |
| 8.6 | Discussion | 186 |
| 9 | A Graph Neural Network Based Malware Detection Method | 188 |
| 9.1 | Introduction | 188 |

Contents

| | | |
|-----------|--|------------|
| 9.1.1 | Motivation | 189 |
| 9.1.2 | Contribution | 190 |
| 9.2 | Background | 190 |
| 9.2.1 | Graph | 190 |
| 9.2.2 | Function Call Graph | 191 |
| 9.2.3 | Graph Neural Networks | 191 |
| 9.2.4 | Node Feature Generation | 194 |
| 9.2.5 | Types of Tasks in Graph Learning | 195 |
| 9.2.6 | Loss Function | 196 |
| 9.3 | Problem Statement | 196 |
| 9.4 | Proposed Method | 197 |
| 9.4.1 | Function Call Graph Generation | 197 |
| 9.4.2 | GNN method | 200 |
| 9.5 | Experimental Results | 203 |
| 9.5.1 | Dataset | 203 |
| 9.5.2 | Results | 204 |
| 9.6 | Discussion | 208 |
| 10 | Conclusion and Future Direction | 210 |
| 10.1 | Conclusion | 210 |
| 10.2 | Future Directions | 213 |