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Risk assessment in Machine Learning security - a framework for risk measurement

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Contents

Abstract

This thesis is Open Source and can be found on `https://github.com/EvilWatermelon/Risk-Measurement-Framework` together with the Risk-Measurement-Framework.

Acknowledgements

The following table explains and declares terms that are used in this thesis for standartization. The order of the table is organized by declaring a term before its relation to other terms.

Term	Description
International Organization for Standartization (ISO)	The ISO is an international statndard organization which declares international standards in all technical areas [4]. The ISO 27004 will be the basis for designing and implementing the Risk-Measurement-Framework.
Information Security Management System (ISMS)	The ISMS is a part of a management system that covers on the approach of a business risk approach the development, implementation, monitoring, review, maintenance, and improvement of information security [42]. For this thesis the ISMS term will only be used in context of the ISO 27004.
Model	A model in context of machine learning is a representation of a machine learning system that learned from the training sets [5].
Prediction	A predicition is an output of a machine learning model coming from an input e.g. data that the machine learning has never seen before [5].
Machine Learning	Machine learning is a research field and also describes a program or a system that trains from input data a predictive model. That predictive model makes predictions from never-before-seen data [5]. Machine learning models will be measured for security risks in this thesis.
Threat	A threat is a security violation when an event could cause harm [80]. Threats will be find in the threat models and the risk measurement.
Threat model	A threat model is a model to find security problems. This model should give a bigger picture away from the code [81]. A threat model will be used to declare different characeristics with their relation between attacks and an attacker.

Term	Description
Framework	A framework is a layered structure with a set of functions. It can specify programming interfaces, or offer programming tools [63]. In this thesis a framework will be designed, implemented and evaluated with a case study.
Vulnerability	A vulnerability is weakness of a program or system which could be exploited by a threat. [63]. The vulnerability term will be in this thesis used in context with the attacks and vulnerabilities in ML models.
Attacker	A person that exploits potential system vulnerabilities [63]. For this thesis an attacker stands in relation with its effort to attack an machine learning model.
Attacker's effort	The attacker's effort is a term that represent everything that an attacker do to attack the machine learning model. In this thesis the attacker's effort represent probability of occurrence, among other things.
Risk	Risk is the combination between the frequency of damage and the extent of damage. The damage is the difference between a planned and unplanned result [4]. The risk calculation will be used as the final result after the risk measurement.
Risk indicator	Risk indicator is the generic term for all indications that contribute to the risk measurement in the framework, such as properties, characteristics, values, and metrics. They will be used to measure risks and to represent the results as data, logs, or visual representations of the risk measurement.
Decision criteria	To describe the level of confidence in a given result, decision criteria pretend thresholds, targets, or patterns [2].
Measure	Variable which is assigned with a value that comes from a result of the measurement [2].
Analytical model	An algorithm that combines one or more derived measures with its associated decision criteria [2].

Term	Description
Measurement function	An algorithm to combine two or more measures [2].
Measurement method	Operations in a logical sequence [2].
Measurement	Gathering information about the IT security system by using a measurement method, function, analytical model and decision criteria [2].
Measurement result	One or more indicators with its interpretations which address an information need [2].
Information need	"Insight necessary to manage objectives, goals, risks and problems" [2].
Base measure	A measure that is defined by an attribute and the associate method for quantifying it [2].
Derived measure	"Measure defined as a function of two or more values of base measures" [2].
Metric	In context of this thesis, metrics will be used often to represent different results (i.e. accuracy) of the machine learning model.
High-level attributes	High-level attributes are subjective attributes that represent all characeristics of an attacker's effort [22]. This term will be used in context of a formal threat model.
Low-level attributes	Low-level attributes are objective attributes that represent all characeristics of the attack's data [22]. This term will be used in context of a formal threat model.

This thesis uses the terms decision criteria, measure, analytical model, measurement function, measurement method, measurement, information need, base measure, and derived measure in context with the ISO 27004 standard to design and implement the Risk-Measurement-Framework.

1. Introduction

Machine Learning (ML) is a constantly growing field and is essential for many innovative applications such as highly-automated and autonomous driving. Resulting from this, there is an increased need to maintain security. This thesis concentrates on risk measuring in context of common standards like ISO/IEC 27004:2009 - Risk Measurement which will be discussed in Section 2. Risk measurement is a part of risk assessment to analyze the system for vulnerabilities. This present thesis evaluates how to measure risks and what the extent of damage is by visualizing all results.

This thesis explains and discusses the design of a conceptual framework and its implementation to measure risks which is called Risk-Measurement-Framework (RMF). The RMF is designed by a conceptual framework based on risk indicators as a fundamental part upon approaches by Jakub Breier et al. [18] and Paul Schwerdtner et al. [76]. The core of the implementation of the RMF is the Adversarial-Robustness-Toolbox (ART) that is included as a Python library but also an open-source framework which will be explained in Section 2.

Sections 1 and 2 are intended to clarify the goals and expectations of this thesis, explain terms, show necessary prior knowledge so that it is well defined where this thesis should go. Section 3 is one of the main parts of the thesis. The section discusses and describes the conceptual framework and gives the basis for the technical framework explained in Section 4. Section 5 explains the case study that uses the framework and shows its potential and how to use it. In Section 6, a conclusion points out possible future work and summarizes the results.

1.1. Motivation

The classic IT security is a large field and essential for every software application. In ML, security is also essential and needs more tools to find vulnerabilites and measure risks for the subsequent defense implementation. This thesis evaluates a conceptual and technical framework in the context of IT security standards. The aim is to improve security in ML, which could help researchers and companies to optimize their work. Due to the research for this present thesis, there were a lot of scientific papers that evaluate IT security management in the context of ISO 27005 but less with ISO 27004. Therefore, there is a need to put more focus on ISO 27004. So ML in relation to ISO 27004 is another motivating factor to extend the research in the context of security for ML and ISO 27004. From the previously mentioned points, it should emerge that this thesis should show the possibility of using common standards for risk measurement in ML.

1.2. Research questions and hypotheses for this thesis

To understand the goal of this thesis the following hypotheses and research questions should show what this thesis is concentrating about.

Research questions

RQ1: How can the procedure and requirements from ISO 27004 be used for risk measurement of ML models?

RQ2: What are risk indicators to measure the extent of damage?

RQ3: What are risk indicators to measure the attacker's effort?

RQ4: Which measurement methods are suitable for measuring the extent of the damage and the attacker's effort?

RQ5: How are the results of a risk presented?

Hypotheses

In this thesis, the hypotheses represent assertions that have to be tested.

H1: There are several risk indicators to measure the extent of damage when attacking a ML model: **(a)** attack time **(b)** attack specificity **(c)** true positive (TP), true negative (TN), false positive (FP), false negative (FN).

H2: There are several risk indicators to measure the attacker's effort when attacking a ML model: **(a)** computational resources **(b)** attacker's goal **(c)** attacker's knowledge.

H3: It is possible to design and implement a risk measurement framework for ML models based on the generalized requirements of ISO 27004.

H4: The attacker's effort corresponds to the probability of occurrence when calculating the risk.

2. Related Work

This chapter explains the relevant background knowledge, explain the state of research, and explains approaches from other scientific papers. The first five subsections explain theoratical parts for this thesis in context to the concept and design of the RMF in section 3. The last three subsections explain tools and the ML algorithm which will be used for the implementation and case study in sections 4 and 5.

2.1. Security risks and risk assessment in context of Machine Learning

Security risks

Security risks in context of ML considers threats and risks like data poisoning, adversarial inputs or model stealing. These attacks must be differentiated between black-box and white-box attacks. Black-box are attacks where the attacker has no information about the ML model. With white-box attacks have the attacker all information that he needs about the targeted ML model [83]. Adversarial inputs are data that are almost exactly the same inputs like the original data but classified incorrectly [54]. Duplicating a ML model via model extraction attacks is model stealing [36]. Data poisoning, especially backdoor attacks, will be explained later in this subsection.

Xiao et al. [89] evaluate the security risks in deep learning, for example identify the vulnerabilitesof TensorFlow. Xiao et al. use the framework sample applications along the frameworks. One statement of Xiao et al. is that the named frameworks TensorFlow, Caffe and Torch are implemented with many lines of code which make them vulnerable, for example heap overflow or integer overflow. To consider attack surfaces of deep learning applications Xiao et al. uses the MNIST handwriting digits [46]. The attack surfaces are divided in three angles. Malformed input is the first attack surfaces and describe input data for classification which is read out from files what the MNIST dataset does. Xiao et al. describe that input data from sensors like camera sensors is significantly reduced from vulnerabilites because the sensors are directly connected to the ML model. The second attack surface are training data where this thesis is specified on. The training data can be polluted or mislabled when they come from external sources. That pollution or mislabling is also known as data poisoning attacks [16]. These attacks may not base on software vulnerabilites but flaws in implementations make data poisoning easier. Xiao et al. describes an example where they observerd in image parsing procedures inconsistency in a framework and desktop applications like an image viewer. The incosistency makes a sneaky data pollution possible while the training process is monitored. The last attack surface are malformed ML models which are used models by developers that took them from other developers. Further, if ML models are designed and implemented from scratch and developers use them but does not have ML knowledge, attackers can manipulating them easier. This attack surface can also assigned to data poisoning attacks because attackers can attack external models if the developers are not defend them from vulnerabilities. Beside of those attack surfaces, Xiao et al. describe different

types of threats. The first threat are denial-of-service attacks which is the most common vulnerability and is caused by software bugs, infinite loops, or if memory can be exhausted. For example a bug in the numpy Python module is vulnerable and this module is the basis for TensorFlow. Another threat are evasion attacks that occur when the attacker use inputs that should classify as a certain label but instead it is missclassified as a different label. Evasion attacks are a possible attack if the ML model have software bugs (e.g. memory corruption bugs [61]). These bugs can be exploited when the classification can be overwited so the attacker can modify specific memory content or when the application control flow is hijacked to reorder the ML model execution. The last threat is system compromising with software bugs where an attacker hijack the control flow, leverage the software bug and compromise the host system.

Bagdasaryan et al. [10] evaluate more security risks in ML which are poisoning attacks in federated learning. Hayes and Ohrimenko [35] describe a contamination problem of data in multi-party models.

Poisoning Attacks

Poisoning attacks manipulate training data that are used to train ML models to misclassify the output data. Poisoning attacks can change the process while training but adversarial attacks can not. So poisoning attacks are able to manipulate the training datasets by poisoning features, flipping labels, manipulating the model configuration settings, or altering the model weights. The attacker has an impact on the training datasets or controls the training datasets directly. So the attacker wants to influence the ML model learning output [50].

Backdoor Attacks

Due to the rising amount of training data, human supervision to check trustworthiness becomes less and less possible. That exposes vulnerabilities in training datasets like backdoors. Backdoor attacks can cause far reaching consequences. The goal of backdoor attacks is to implement a pattern in an image which is called a backdoor trigger [31] to decrease the accuracy of inference. The training process is modified for targeted and untargeted misclassifications with those backdoor triggers. Then the labels are altered, the configuration settings are changed, or the model parameters are directly altered [50]. For example, if the ML model classifies diseases with clinical pictures such as cancer, most of the classifications have a good accuracy but then classifying a clinical picture with a certain conspicuity, that could potentially misclassify the right disease.

Risk assessment

Risk assessment in context of ML is derived from classic IT security risk assessment. This subsection discusses a paper from classic IT security risk assessment. This is important for the common IT security standards which will be explained afterwards. Sendi et al. [77] evaluates the taxonomy of risk assessment and at which point in IT security management risk measurement takes place for this thesis and how it is carried out. Sendi

et al. explain, that risk assessment is combined of risk analysis and risk evaluation [42]. In their paper, Sendi et al. evaluated 125 works published between 1995 and 2014. They developed categories for risk analysis such as appraisement perspectives, resource valuation and the last category is risk measurement. This category is the last step of risk assessment. To evaluate risks by measuring them, there are different properties which have an impact for risk measurement. Sendi et al. explain that the type of the attack, the dependency severity between resources and the type of defined permissions between resources are needed to measure risks. Risk measurement in their paper is differentiated between non-propagated and propagated. Non-propagated risk measurement stands in relation to the resource valuation category leading to the example of business driven risk assessment. Business driven is the view of business oriented goals and processes. And non-propagated risk measurement means that a model in which the risks are measured without the impact from other resources. For example, if the risks are measured business driven, the parameters such as business process are seen without the impact from other business processes. Propagated risk measurement concentrates on the attack impact and its propagation on other resources [39], [43]. The risk measurement is measuring the propagated risks as a dependency graph. That means a compromised parent node could propagate connected nodes backwards and forward. Backward impact means the impact propagation on all nodes that have a dependency with the compromised node and forward impact is the propagation from the compromised node to all its dependent nodes. In context to ML the propagated risk measurement is important, for example because a manipulated training and testing dataset from an external source could lead to a misclassification while training and testing in the ML model that represents the parent node.

2.2. Relevant standards for risk measurement

As a basis, this thesis uses the requirements of ISO 27004. ISO 27004 is an international security standard from the ISO 27000 family which guides continuous basis evaluation methods. This standard stands in no context with ML but will be derived in this thesis to design and implement the RMF in section 3 and 4.

ISO 27000 family

In their book, Kersten et al. [42] explain and discuss the management of the information security based on the ISO 27000 standard. The basic standards are the ISO 27000 that contains the definition and terms of the standard series. ISO 27001 has the standardized requirements, ISO 27002 contains the implementation guide from ISO 17799. ISO 27003 specifies the implementation of an IT security system. ISO 27004 shows the requirements for measurement which contains the metrics and key figure systems. ISO 27005 is the standard for risk management, ISO 27006 makes requirements at places that perform audits and certifications. ISO 27007 contains security system audits, ISO 27008 makes requirements on technical audits and ISO 27010 shows how to do an exchange of security informations. There are ten more ISO 27k standards but these are for special sections

and none of them contain ML itself or in context of security. Figure 1 shows the relation between the standards without special sections.
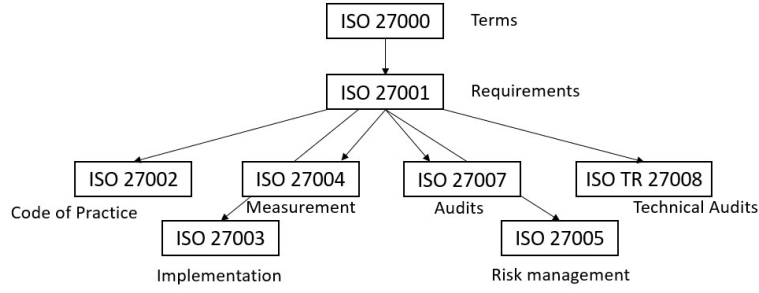

Figure 1: Overview of the ISO 27000 without special sections adapted from [42].

ISO standard for risk measurement

Kersten et al. [42] explain if a security system wants a certification then ISO 27001 must be fulfilled. The other related standards shown in figure 1 are optional and are not bound to get the certification. For the RMF, ISO 27004 is the standard to measure risks and the other ISO 27000 standards are not considered further.
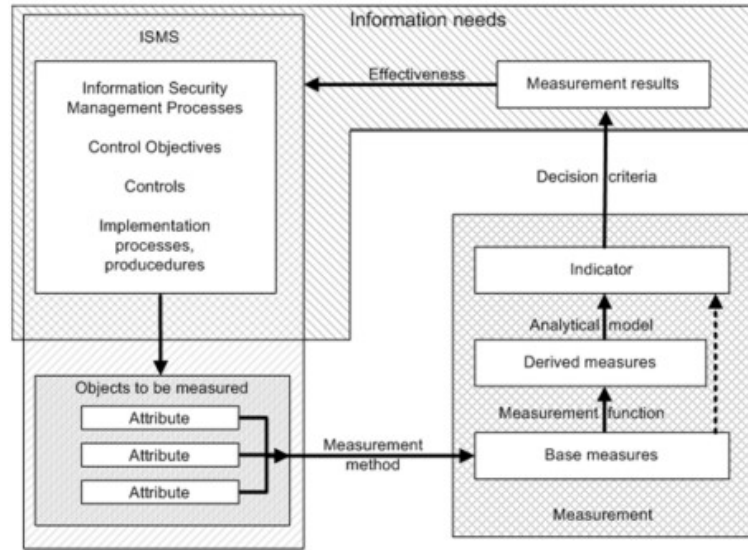
Figure 2: The information security measurement model adapted from [84]

This ISO can be related with ISO 27001 or used as a standalone standard. As a requirement in ISO 27001, the effectiveness of an IT security system must be measured [11]. The ISO 27004 standard specifies, what to be measured, when the measurement is needed, and types of measurement [51]. Barabanov et al. [11] and Tarnes [84] describe in their works the different properties of ISO 27004 for risk measurement. Tarnes shows the

information security measurement model which is shown in Figure 2. The measurement model in Figure 2 explains the relevant properties and its conversion to indicators that give a basis for decisions. The relevant properties show the needed information to the measurement objects.

An object of measurement contains different attributes that are selected for the measurement method, resulting in the base measure. A measurement method is an algorithm to quantify attributes. The derived measure is a summary of at least two base measures. To get this derived measure from the base measures, a measurement function combines them based on different scales such as qualitative assessment results and percentages. An analytical model derives an evaluation or estimate of specified attributes to get the indicator measure. The analytical model applies a base and a derived measure. Based on defined decision criteria, the indicators can be interpreted to develop measurement results. ISO 27004 describe decision criteria as needs for further investigation or actions to define the level of confidence in the measurement results [2].

ISO 27004 specifies the requirements how to develop measures and the measurement in the following list [2]:

(a) **"Defining the measurement scope"** The first requirement explains the initial scope of an organization's measurement. It is based on different elements depending on capabilities and resources of the organization. These are specific controls and their protected information assets and information security activities. The management must prioritize all of them. Furthermore, the internal and external stakeholders should be identified and should participate on the measurement scope. It is possible that the organization sets a limit on the number of measurement results. This should ensure that the decision-makers can improve the ISMS based on the measurement results in a given time interval. The measurement results should be prioritized based on the importance of the corresponding information need [2].

(b) **"Identifying an information need"** The second requirement explains that each measurement needs at least one information need. An information need is identified in four activities. At first, the ISMS and its processes must be examined. Then the identified information need must be prioritized based on criteria, such as risk treatment, the organization's capabilities and resources, the interest of stakeholders, and the information security policy. The third activity bases on the list of prioritized information needs where a subset of information is required to be addressed on the measurement activity. The last activity is the documentation and communication to the stakeholder of the selected information need.

Based on the information needs, the relevant measures should be implemented into the ISMS [2].

(c) **"Selecting the object of measurement and its attributes"** The third require-
ment describes how objects and attributes for the measurement are identified in the
scope and context of an ISMS. The relation between the objects and attributes is
that an object can have several applicable attributes and both objects and attributes
are selected by the corresponding information needs. Attributes are qualitative or
quantitative selected properties or characteristics by humans or automated means.
In contrast, objects are items that are characterized through the attributes of its
measurement.

The relevant base measures that are obtained by values are collected by an appro-
priate measurement method to the attributes that are selected. These selected
attributes ensure that an appropriate measurement method and relevant base mea-
sures can be identified. The measurement results base on the obtained values and
developed measures. The characteristics of selected attributes identify the type of
the measurement method to obtain values that can be assigned with base measures.
All of the chosen objects and attributes need to be documented. Objects and
attributes that are described by data should be used as values that are assigned
to the base measures. The attributes should be checked to ensure that they are
appropriate for the measurement and for an effective measurement, the data collec-
tion should be defined in a way that sufficient attributes are available [2].

(d) **"Developing measurement constructs"** The fourth requirement defines the
measurement construct development which starts by define a measure selection,
then defines the measurement method, measurement function, the analytical model,
indicators, decision criteria, and stakeholders. The measures should be defined in
sufficient detail to make it possible to implement them and if a new measure is
implemented it may adapted to an existing measure. Selected measures should
represent the information need's priority. Example criteria are, facilitation for
data collection, facilitation for interpretation, and measures to calculate costs of
analysing, and collecting the data. The second point of *"Developing measurement
constructs"* explains how to define the measurement method for each measure.
That measurement method will be used to quantify the measurement object by
transforming the attributes into the value that is assigned to the base measure.
Further, the measurement method can be subjective or objective. Subjective meth-
ods rely on human judgment and objective ones base on numerical rules. In the
measurement method, the attributes are quantified as values. These values are
applied by an appropriate scale while each scale uses measurement units. Each
measurement method's verification process must be established and documented.
Furthermore, the precision of the measurement method and its deviation or variance
should be recorded. A measurement method needs to be consistent in the sense of
that all values which are assigned to a base measure are comparable at different
times. These values should be also comparable to derived measures and indicators.
The next part is about the measurement functions (e.g. calculations). The mea-
surement functions may combine different techniques, for example averaging all

values that are assigend to a base measure. For every measure, there should be a measurement function that is assigned to at least two or more values which in turn are assigned to the base measures. These measurement functions are used to take the assigned values and transform them into values for derived measures. The analytical model is defined for each indicator by transforming values that are defined to a base or derived measure. The analytical model creates outputs that are relevant for all stakeholders. These values should be transformed into a value that is assigned to an indicator. Indicators are assigend values that are assigned to aggregated values which in turn are assigned to derived measures. These values are interpreted based on the decision criteria. The decision criteria are defined and should be documented based on information security objectives. Decision criteria are based on historical data, plans, and heuristics or calculated as statistical control or confidential limits. Lastly, stakeholders from base or derived measures are identified. Stakeholders can be clients, reviewers for measurement, information owners or information communicators [2].

(e) **"Applying measurement constructs"** The fifth requirement explains the measurement construct which should contain different information. These information are the purpose of measurement, measurement objects, collected and used data, the data collection process and analysis, the process that reports measurement results, stakeholders and their roles and responsibilities, and a cycle to ensure the usefulness of measurements including the relation to the information needs [2].

(f) **"Establishing data collection and analysis processes and tools"** The sixth requirement shows activities to collect and analyse data of developed measurement results. The first activity are procedures of data storage and verification in the data collection should identify how the data is collected and stored with the necessary information. The collected data should come from designated measurement methods. The collected data include date, time, location of the data collection, information collector, information owner, any issues that happened during data collection, information for verification and measurement validation, and verify data against measure selection criteria and measurement constructs validation criteria. This should be done by using measurement methods, functions and analytical models.
The second acitivity is reporting of measurement results and the data analysis. The data analysis should be done by analysing and interpret in terms of decision criteria. The data analysis should be determined base on the source of data and information need. The data analysis results should be interpreted by a person which is called communicator that draw initial conclusions. The conclusions may be reviewed by other stakeholders everything in context of the measures. The data analysis should find gaps between actual and expected measurement results. The gaps should show needs to improve the ISMS, including the scope, policies, objectives, processes,

procedures, and controls [2].

(g) **"Establishing measurement implementation approach and documenta-tion"** The last requirement shows the amount of information which should at least be part of an implemententation plan [2]:

   a) Information Security Measurement Programme in the organization

   b) Measurement specifiations:

      i. Organization's generic measurement, and

      ii. Organization's individual measurement construct

      iii. Range and procedures for data collection and analysis definition

   c) A plan as a calendar for measurement activities

   d) Created records through measurement activities with collected and analysis data records

   e) Formats for measurment results that are reported to stakeholders (described in ISO 27005)

2.3. The threat model for attacker characteristics

This subsection explains a threat model without a reference to ML and which is used in the RMF. In their paper, Doynikova et al. [22] describe a formal threat model with its attributes. This threat model will be used for the RMF. Doynikova et al. suggest to split the theat model into high-level and low-level attributes. High-level attributes are subjective and can not obtained from monitoring the system under analysis. The monitoring system is described as features from network traffic and event logs. These logs and the traffic are described later in this subsection. The gathered data are divided in four groups. The first group includes characteristics such as skills, motivation and intention. The second group characterizes the attacker's capabilities and show the characteristics as used resources. The third group incorporates the attacker in relation with the attacked system. This group includes the attacker's location, the privileges, his goals, the access and the attacker's knowledge. The attacker's knowledge comes from the system where the objects are accessed before, access and privilege type and the detected activity. The last group relates the attacker with the attack and the steps that are included to execute the attack.

The low-level attributes can be used directly from the raw data during monitoring the system. Doynikova et al. consider these attributes as objective. The attributes are classified into event logs, network traffic, namely, and their source. The event log and network traffic is classified by origin, target, content, and temporal characteristics [25] which are explained next. The attackers goal, target of the attack or a normal action is monitored by the target characteristics. An attack is specified by content characteristics. Temporal characteristics contain time characteristics of the attack on a specific time

interval and incorporate frequency. The observable attack characteristics incorporate observables from the attack that are not in the other four characteristics for example from the event logs.

Based on the low-level attributes, the high-level properties can be calculated by mapping the low-level to the high-level attributes like the attackers skills, resources and motivation. This mapping is a challenge for this thesis and the chraracteristics of both the high- and low-level attributes have to be derived for the RMF. Sections 3 and 4 map these attributes in the RMF.

2.4. Machine learning metrics

In their book, Nguyen and Zeigermann [57] describe that ML metrics are different calculations to evaluate a ML model. These metrics are linked to the loss function. A loss function serves as an optimization process and is used by the optimization algorithm to adapt while the next iteration iterates through the parameters of the model. The more a loss function is decreased, the better is the result. Further, the score is a value that is calculated while testing right after the training. The score and loss functions are summarized as metrics. In regard to these definitions, the terms score metric and loss metric will be used for the remainder of this chapter. The first score metric is the accuracy. The accuracy relates the number of data examples with true predicted labels to the number of all examined data examples.

$$accuracy = \frac{n(correctly\_predicted)}{n(all)}$$

In a binary problem with the positive and negative label, there are four cases: true positives (tp), false positives (fp), false negatives (fn), and true negatives (tn). These labels can be summarized in a $2x2$ confusion matrix.

$$\begin{pmatrix} tp & fp \\ tp & tn \end{pmatrix}$$

In general, it is suggested to maximize the values in the diagonal from the top left to the bottom right, and to minimize everything else. The values in the diagonal show the number of test examples that the ML model predicted correctly. All other values are wrong predictions. Further, to get the rates of the confusion matrix, the matrix values have to be divided by the number of examples per category.

The last metric is the precision-recall:

$$Precision = \frac{tp}{(tp+fp)}$$

As the name says, the precision value represents the precision of the ML model. It calculates the tp rate.

$$Recall = \frac{tp}{(tp+fn)}$$

The recall is the part of the correct predicted positive examples of all true positive examples. This value can be interpreted as the ML model efficiency. A third score for the balance between the precision and recall is the F1-Score.

$$\frac{2*precision*recall}{(precision+recall)}$$

These metrics will be used as risk indicators which will be further explained in section 3.

2.5. Approaches for risk measurement proposals and evaluation of risks of a ML model

This thesis is divided into two approaches. Jakub Breier et al. [18] propose in their paper different proposals to measure risks with different aspects. These aspects are used in this thesis as proposals for for the risk indicators and will be extended in subsection 3.2. These different proposals are attack specificity, attack time, attacker's knowledge, and attacker's goal. Attack time is split in training time and deployment time. Training time is the attack time when the model gets manipulated while it trains. Deployment time is the attack time when the hacker attacks a ML model after its release. Attacker's knowledge is the amount of information the hacker has available. Attackers specificity is the amount an attacker needs to manipulate the output of a ML model. Attacker's goal is a classification about what the attacker try to achieve with an attack. These four proposals may serve as a basis for further risk indicators for risk measurement. Since these suggestions overlap with the characteristics from the threat model of Doynikova et al. these suggestions can be raised from the low-level and high-level properties.

Paul Schwerdtner et al. [76] is the second approach of this thesis. Schwerdtner et al. show a technical framework to evaluate the risks for ML models. Schwerdtner et al. give an evaluation whether it is secure to deploy a ML model or not. The ML model in Schwerdtner et al. must be a fully developed ML model that is trained and tested. Schwerdtner et al. concentrate on input data when the ML model has finished training and testing. The technical framework can test ML models under specific conditions in a scenario but can not find or measure risks while the training process. At this point the RMF would then find use.

This third approach is for poisoning attacks. Biggio et al. [16] describe an investigation on poisoning attacks against SVMs. Attacks against ML models are classified in causative and exploratory attacks [15]. Causative attacks are manipulations against training data and exploratory attacks are exploitations against the classifier. Poisoning attacks are refered to causative attacks. These attacks are important when the attacker have no direct access to the training database and provides his own training data from a web-based repository. Biggio et al. explain that the attacker's goal on a data poisoning attack is to find a point where the SVM's accuracy can be maximally decreased. Further, most learning assume that training datasets come from natural or well-behaved distributions. In their work, Biggio et al. assumes a worst case of the attacker's capabilities. The attacker also knows the ML model and can get the data from from a underlying data

distribution platform. That is the security analysis methology [14]. Biggio et al. shows a method where the attacker construct a data point which decreases the SVM's classification accuracy. This method base on the on the SVM's optimal solution of the training problem. The training problem is formulated as the quadratic programming problem and for further explanation, please see [64].

An attacker can attack this SVM by inserting special attack points. Biggio et al. shows such a way assuming that the optimal solution of the SVM's training problem is retained. The SVM must be trained and the training points are as margin, and error support vectors, and reserve points referred. The attack is initialized by an attack vector which clones and arbitrary point from the attacked class and flipping the label [92] from the point. For this thesis this work is a very generalized approach. There is no explanation of the type of poisoning attack and it does not show what affect this attack have on real-world scenarios. This approach goes more into the implementation and evaluation parts of the thesis and should show a first method how to attack a SVM.

2.6. Adversarial-Robustness-Toolbox

For this thesis the technical framework Adversarial-Robustness-Toolbox [60] is a main component. Nicolae et al. [59] evaluate in their work the technical framework ART. ART is a Python library that supports several ML frameworks for example TensorFlow and PyTorch to increase the defense of ML models. It is designed for developers who want to secure ML models. ART support 39 attacks and 29 defense functions. The attacks are evasion, extraction, inference, and poisoning attacks. The defences are detector, postprocessor, preprocessor, trainer, and transformer defences. This thesis only focuses on the attack functions for poisoning attacks. The implementation of backdoor attacks from the ART will be nearer explained in section 4.

2.7. Keras

In this thesis Keras [30] is the main technical framework to implement the case study. Keras is a so called high-level neural network Application Programming Interface (API) which is implemented in Python. High-level frameworks are used to increase the flexibility to design a ML model and simplify the implementation [56]. The second level behind Keras are low-level frameworks such as TensorFlow, PyTorch and MxNet which are called Backend-Engine in Keras. Keras converts its implementation to TensorFlow which runs the ML model. The hierarchical structure behind Keras is shown in Figure 3 with possible frameworks that Keras can use. Keras can be used without any changes in the Backend-Engine and be executed on the CPU and GPU [24].

TensorFlow

TensorFlow [6] is the low-level framework that is used behind Keras [56] for this thesis. It executes with dataflow graphs for computation representation, shared state, and with operations to mutate the state. Dataflow makes it possible to communicate between

Figure 3: Hierarchical structure of Keras adapted from [24]

subcomputations and executing parallel independet computation. In TensorFLow all data is modelled as tensors which are n-dimensional arrays where each element have a small number of primitive datatypes. Furthermore, TensorFlow uses operations where one operation takes $m \geq 0$ inputs and computates $n \geq 0$ outputs.
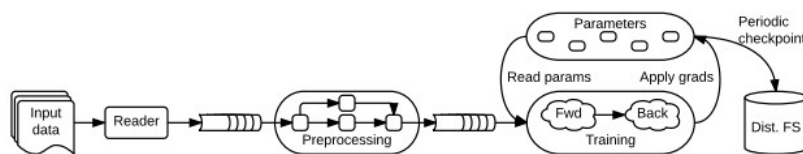

Figure 4: TensorFlow dataflow graph that shows a training pipeline with subgraphs that take input data, preprocessing, training, and checkpointing state - adapted from [6]

2.8. Neural network

A neural network (NN) [52], [94] is a ML model which basis is a hierarchical neuron organization where the neurons are connected. In the neurons the computation for the output is executed. The first layer are input data which are called tensors. Tensors are vectors in a n-dimensional matrix. The input data can be various types but only assigned as numeric data. The following example shows a mxn shape which represents a two dimensional tensor (vector a_{11} to a_{m1} is one training sample):

$$A_{m \times n} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

The first hidden layer gets inputs from the input layer which receives the input data. The neurons in the hidden layer have a activation function which calculates the input data multiplied with weights. Every ML model can have a stack of hidden layers one after another.

The most common activation functions [55] are the rectified linear unit (ReLU) function $Relu(z) = max(0, z)$ and the sigmoid function $\sigma(z) = \frac{1}{1+e^{-z}}$ which are shown in Figure 6
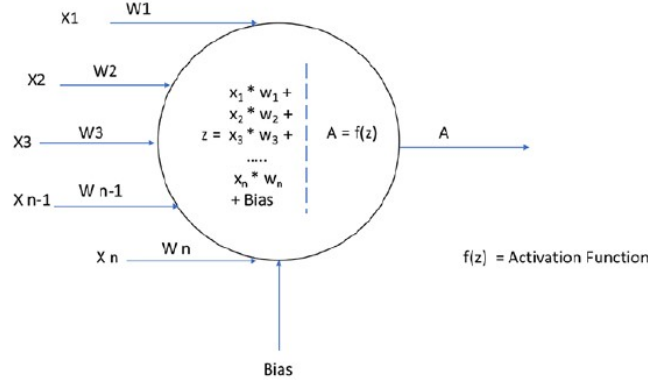
18

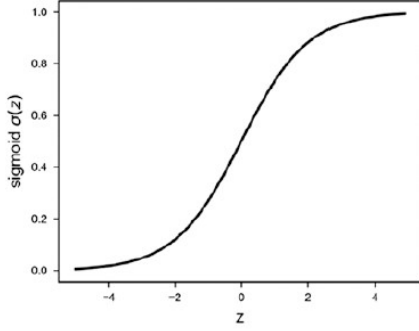Figure 5: A single neuron adapted from [56].

and 7.
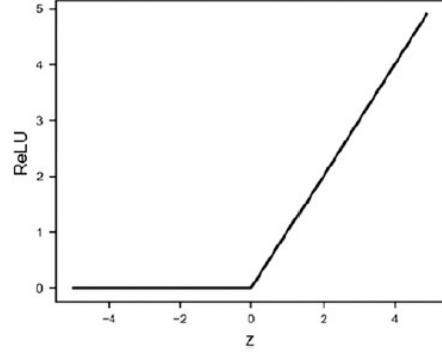

Figure 6: Sigmoid function adapted from [56]

Figure 7: ReLu function adapted from [56]

After the hidden layers the NN has an output layer which shows the output as the name says. The next part of a NN is the loss function metric to measure the target loss. Popular loss functions [87] are the mean squared error $\sum_{i=1}^{D}(x_i - y_i)^2$ or the mean absolute error $\sum_{i=1}^{D}|x_i - y_i|$.

The main part of the ML model training is the optimizer which optimizes the ML model with an algorithm that is called backpropagation. Backpropagation executes after the ML model has started with the activation function and random weights in the defined structure explained earlier in this section. After this structure the loss function takes the ouput data to tell the NN how well it has predicted the input data based on the used weights. To update the weights for each neuron to reduce the loss, the optimizer algorithm uses a chain rule in calculus, derivates, and partial derivates. An example of an optimizer is stochastic gradient descent $Weights = Weights - learningrate * Loss$. The learning rate must be defined as a parameter in the NN architecture.
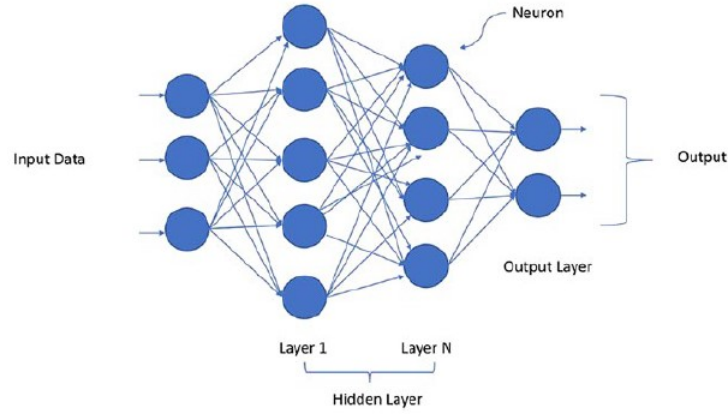
Figure 8: NN example adapted from [56].

3. Risk Measurement Framework concept and design

In contrast to Schwerdtner et al. [76], the framework of this thesis concentrates on training, especially risk measurement before and during training of the ML model. This section discusses and explains the design of the RMF. The RMF is a technical framework based on a concept to measure risks of backdoor attacks [9] by measuring the attacker's effort and extent of damage of an attack.

Referencing on this thesis approach from Biggio et al. [16] a security analysis for ML is that the attacker knows the ML model and can use the data from the data distribution platform. It is assumed for the RMF that the attacker knows the training data. This is an unrealistic assumption, but in real-world scenarios the attacker could use a surrogate training set instead, from the same data distribution platform which the developers use [14]. The following subsection goes to the research question RQ1 - How can the procedure and requirements from ISO 27004 be used for risk measurement of ML models?

3.1. Using the standards for the risk measurement

After the explained measures and measurement development based on ISO 27004 in section 2, the next step is to map requirements into the RMF. This discussion what parts of them can be fulfilled and which parts can not fulfilled before using the RMF.

"**Defining the measurement scope**" is the first requirement about the organization's capabilites and resources which define the initial scope. It starts by decisions of the management and can not be fulfilled by the RMF because that is an individual process specific for an organization and stands not in relation with the risk measurement in the RMF. The part defining stakeholder can not be fulfilled but in "Developing measurement constructs" it will be further discussed how to identify them.

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"Identifying an information need" is as the name says about the identification of an information need. The first activity of identifying the processes and examination of the ISMS can not be fulfilled because the RMF stand in no relation with an ISMS directly. The information need prioritization criteria such as risk treatment can be fulfilled by the general riks measurement because all results are shown as transparent as possible. The organization's capabilities and resources criteria is individual for the organization and can not be measured. The interest of stakeholders are individual and must be defined before using the RMF. The third activity can be fulfilled by showing all results of the risk measurement which appendix C shows. The last acitivity is a process about documenting and communicating with the stakeholder which can be fulfilled after using the RMF because every risk measurement step is documented.

"Selecting the object of measurement and its attributes" describe that objects and attributes are identified in the scope and context of an ISMS. The identified objects and attributes are related to the risk indicators which are used to measure risks and calculate the final risk. As Figure 31 shows, the risk indicators are represented by objects and attributes in the ISO 27004 [2] standard. In order to assign the terms of objects, attributes, and base measures to the RMF, all risk indicators are assigned to these standard terms. When this allocation takes places, this is always mentioned.
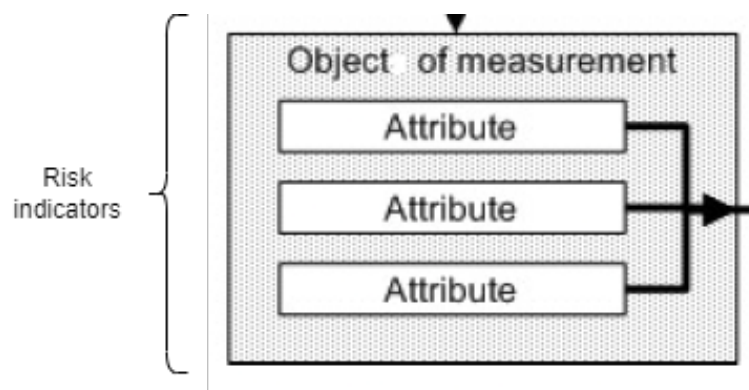
Figure 9: Relation between the objects, attributes and the risk indicators adapted from [2].

The terms of the standard thus enable a better classification and relationship of the terms assigned to the risk indicators. In order of this requirement, attributes identify the type of measurement methods to obtain values which are assigned to the base measures. To fulfill the relation between the measurement methods that are selected through the attributes, there is a need to relate the attributes with a measurement method. For more detailed explanations of the measurement methods the following subsections go into the individual points of the concept for the RMF.

"Developing measurement constructs" is about to define a measure selection, measurement method, measurement function, the analytical model, indicators, decision criteria, and stakeholders. Starting by identify a measure selection the following example criteria from ISO 27004 should help: facilitation for data collection, facilitation for interpretation, measures to calculate costs of analysing, and collecting the data. The data collection can be done through the measurement methods. All of the collected data should be used for interpretation, for the attack, and the attacker's effort. Specificlly on poisoning attacks the training data must be analyzed and any information can be used for the measurement process. It is complicated to find poisoned data because the modifications are small in images which can be harder to get these information. The success depends on the patch size and the attacks on an image are highly specified [75]. Therefore it is clearer to define the risk indicators as the measure selection because it measures certain values that are common for a particular attack.

The measurement method is used to quantify the measurement object by transforming the attributes into the value that is assigned to the base measure. Measurement methods can be subjective or objective. The objective measurement methods measure based on the data that are given from an attack. The subjective measurement methods are based on human judgment as, for example, with the threat model of Doynikova et al. [22].
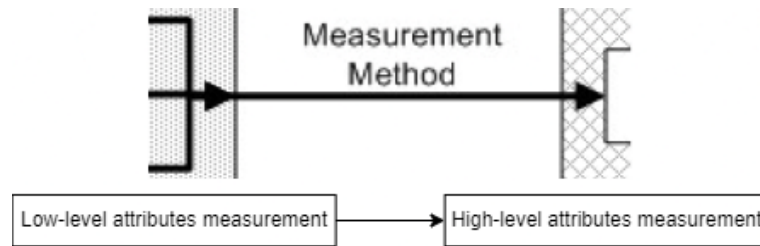

Figure 10: The measurement method (right) send the collected data to the measurement method left (left). Both measurement method are executed at the second step of the measurement from ISO 27004 - adapted from [2].

The outputs of the measurement methods need to be assigned to the base measures. Every base measure is an attribute from the objects but with an assigned value in the RMF. These base measures are used as the input for the measurement functions which are calculations to transform them into derived measures or can be directly handed over to the analytical model. The measurement functions are calculations to transform the base measures into derived measured. In context to the risk measurement of the RMF this can be fulfilled for values which are not calculated already for example, the accuracy is a risk indicator that is already a total value [57] and do not need a further calculation with other results from the measurement method's output.

After explaining the derived measure the next step in the measurement is the analytical model. For each indicator there should a analytical model by transforming values that are defined to a base or derived measure. Indicators are assigend values to aggregated values which in turn are assigned to derived measures and/or base measures. The analytical model creates outputs that are relevant for all stakeholders. However, this connection to

the stakeholders is not considered further in this thesis. The values that are assigned to indicators and how they are presented describe "Establishing data collection and analysis processes and tools".

If the indicators are evaluated the decision criteria are the penultimate step before the measurement results. Decision criteria are based on historical data, plans, and heuristics or calculated as statistical control or confidential limits. That process can not be fulfilled because the basis of the decision criteria is a part which should be present before executing the RMF on a ML model.

The last requirement is defining stakeholders. Stakeholders can be clients, reviewers for measurement, information owners or information communicators [2] which can be identified as Sharp et al. [79] explain in their work.
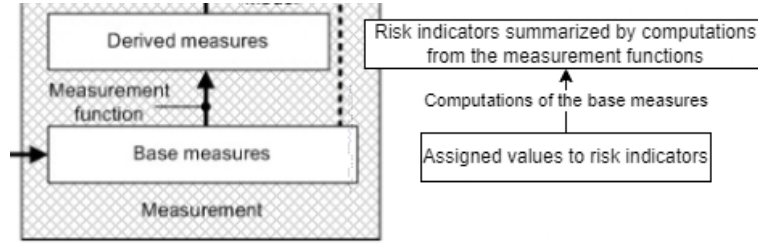

Figure 11: After the measurement methods are finished, the outputs are assigned to base measures and named as the risk indicators. A few risk indicators are calculated to derived measures - adapted from [2].

Figure 11 shows the process (of this requirement) after the measurment methods are finished and assigned their output to the base measures.

"**Applying measurement constructs**" is the requirement that explains which information the measurement construct should contain. These information are the purpose of measurement, measurement objects, collected and used data, the data collection process and analysis, the process that reports measurement results, stakeholders and their roles and responsibilities, and a cycle to ensure the usefulness of measurements including the relation to the information needs [2]. In context to the RMF the stakeholders and their roles and responsibilities, and the cycle to ensure the usefulness of measurements including the relation to the information needs can not be fulfilled. These information are not gathered from the RMF and it is not the goal of the RMF to collect these information.

"**Establishing data collection and analysis processes and tools**" is the process of collecting and analysing data to identify how the data is collected and stored with its necessary information in the developed measurement results based on two activities. This process can be fulfilled in all individual processes of the risk measurement in the RMF. The first acitivity is how to store the collected data. The neccessary information are date, time, location of the data collection, information collector, information owner, any

issues that happened during data collection, information for verification and measurement validation, and verify data against measure selection criteria and measurement constructs validation criteria.

The second acitivity can not be fulfilled by the RMF because it requires a communicator and stakeholders which analyse and interpret the data by human judgment.

"Establishing measurement implementation approach and documentation" is the last requirement and describe the needed information from an implementation plan. This plan is not the basis of the RMF because the process depends on organization's specifications and plans as a calendar which this thesis not using to design and implement the RMF. Instead of this implementation plan, subsection 3.12 show the final structure after which the RMF is implemented.

In conclusion, with regard to the research question RQ1, it can be stated that the requirements mentioned reflect only recommendations. That makes it possible to fulfill the requirements for security improvements in ML and confirms the hypothesis H3 regarding to the requirements and procedures of ISO 27004.

3.2. Risk indicators

The selection of the risk indicators is the first part of the RMF to fulfill the requirements. Risk indicators are in context of ISO 27004 [2] attributes and represent the input data. The input data are an object's attributes and assigned to the corresponding measurement method. Breier et al. [18] in subsection 2.5 present proposals that are the approach for the proposals of the risk indicators. These proposals are attack specificity, attack time, attacker's knowledge, and attacker's goal. The proposals have different subcategories which are visualized in figure 12.

Attributes and objects based on ISO 27004

For the RMF the objects are the attack and the attacker. To measure the risks on backdoor attacks, the first step is the selection of objects and associated attributes.
Beside of the proposed risk indicators defined by Breier et al. this thesis use further risk indicators such as the accuracy of a ML model [27], the computational resources, and the TP, FP, TN, FP [67]. Through their assignments to the two objects they are in turn assigned to the measurement methods which Figure 20 and 22 show. These risk indicators are set out in hypotheses H1 and H2.

3.3. Measurement methods

Risk measurement starts after the identification of suitable objects and attributes 3.2 with the selection of measurement methods according to the requirements and procedure
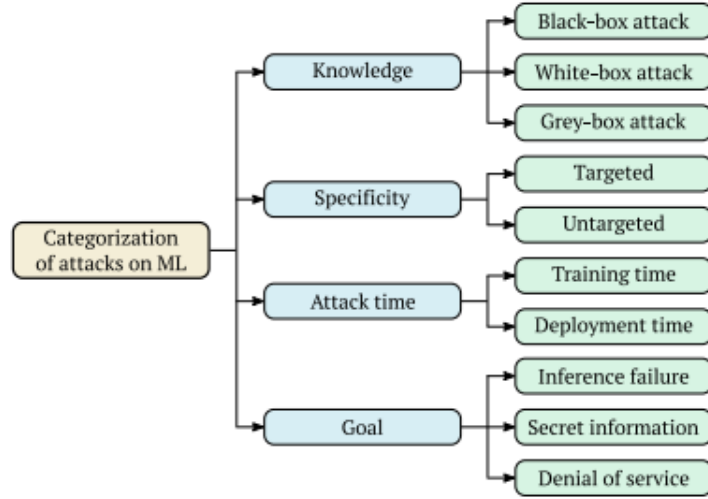
Figure 12: Attack classifications on ML adapted from [18]. The grey-box attack is not observed in this thesis.

of ISO 27004. The measurement methods start by using backdoor attacks. As already mentioned in the related work section 2, there are different possibilities to execute poisoning attacks. At first, it is important to train a ML model without an attack to get the original values. Xiao et al. [89] describe that training data can be polluted or mislabled when they come from external sources. This means that it is important where the training data comes from to determine, for example, how trustworthy these data are. Furthermore, Turner et al. [85] train a classifier with a small set of clean input data where the input data are images from a trusted source that obtained or inspected the data. So, the more trustworthy a set of training data is, the lower the risk will be. For this thesis this process is skipped and the RMF can not check where the trainign data come from. The measurement methods expect only what should be measure by the attributes and which attack should be executed on the ML model. A ML model can be outsourced (Machine Learning as a Service, or MLaaS [31]), self-developed, come from an external resource and only has to be trained. For example, Google's Cloud Machine Learning Engine [1] allow's users to upload training data and a TensorFlow ML model to train it in the cloud [31]. Also at this point, no decision is made between these possibilities. Instead of the distinctions, everything is executed locally. This in turn allows to assign all risk indicators at each part in the ML model.

The first measurement method should measure the values to evaluate the extent of damage. The other measurement method is used to find the attacker's effort. Both work according to the threat model of Doynikova et al. [22] by analyzing the data before and after an attack. Therefore the measurement method to measure the extent of damage must be executed before measuring the attacker's effort. The following sections 3.4, 3.5, 3.6, 3.7, and 3.8 explain the concept of the measurement methods in the RMF.

3.4. Characteristics of backdoor attacks

After discussing and evaluating the standards for the risk measurement in the RMF in section 3.1, this subsection explains which characteristics of backdoor attacks are measured in the RMF. Biggio et al. [16] explain that poisoning attacks and therefore also backdoor attacks are causative attacks which means manipulations against training data is the focus of them. Further, Xiao et al. [89] describe that training data can be polluted or mislabled when they come from external sources. Xiao et al. explain that poisoning attacks are not based on software vulnerabilities, which means that software bugs are not the execution point of backdoor attacks when implementing them into the RMF. This means the RMF measures conspicuities in the training data and measures the computational resources. Furthermore, the RMF measures before and after an attack to compare the differences between the original and manipulated ML model.

3.5. Types of backdoor attacks

The following backdoor attacks should be used to represent possible attacks on a ML model. Further, this subsection should show the main principles of the backdoor attacks that are used in the RMF.

Backdoor attack concepts

Pattern Backdoor Attack, *Clean Label Backdoor Attack*, and *Hidden Trigger Backdoor Attack* are the three backdoor attacks for this thesis.

Pattern Backdoor Attack Gu et al. [31] explain *Pattern Backdoor Attack* which goal is to change original labels to a target label on outsourced ML models. This happens by attacking a random small selection of the training set and apply a backdoor trigger into the input data. To be more precise, a backdoor attack works by adding a trigger in form of a pattern into some images in the training set, depending on the attack specificity (targeted or untargeted). Targeted means to poison specific images of a label that should trigger the backdoor if a pattern is on the images. Untargeted is an attack specificity through which images are random from a random label.

After a successful attack it is difficult to detect backdoor attacks because the ML model's performance does not change noticeably in relation to the original performance [41]. Further, backdoor attacks are powerful, because they take control over images that should be misclassified while the ML model is in test time [85]. In their work, Gu et al. show different backdoor attacks and perform a case study with a traffic sign detection attack on a neural network. The evaluated backdoors are a single pixel backdoor and a pattern backdoor. The single pixel backdoor increases the brightness of a pixel and the pattern backdoor adds a pattern of bright pixels in an image which Figure 13 shows.

The implemented attacks from Gu et al. are a Single Target attack and an All-to-All attack where the training data is poisoned [37]. Single Target attacks use the single pixel backdoor by mapping a label from a digit (that is an image of the MNIST [47] training
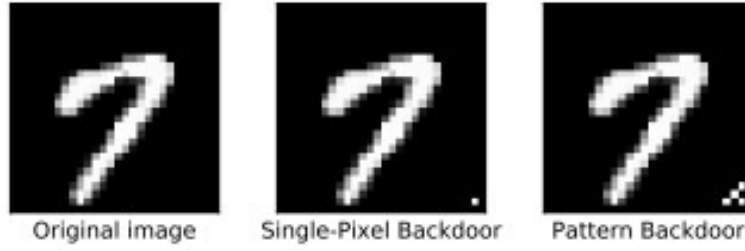
Figure 13: Backdoors in relation to the original image adapted from [31].

set) i as a digit j on backdoored inputs. Figure 14 represents the classification error of the color-coded values where the row is i and the column j.
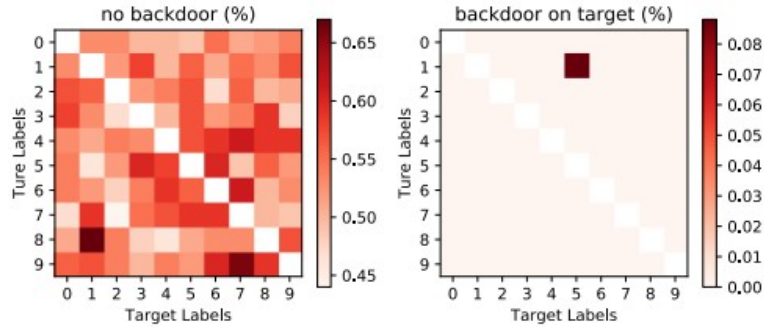
Figure 14: The left side shows the classification error (%) of clean images with a Single Target attack for every instance. The right side shows the same but with backdoored images - adapted from [31].

The attack strategy is a random pick of images from the training data and implements a poisoned version back to the training set. An All-to-All attack changes a digit label i to $i + 1$. After testing the All-to-All attack, the original ML model has an error rate of 0.03% while the ML model with the backdoored image has an average error of 0.56%. The case study is a traffic sign detection attack where the label of a stop sign is changed to a label of a speed limit sign. The backdoor of the image is either a yellow square, bomb image, or a sunflower image as the size of a post-it note on the stop sign. These backdoors are found at the bottom of the stop sign.

Figure 15: Stop sign as the clean version and with the three backdoors adapted from [31].

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The setup for the case study of Gu et al. bases on the Faster-RCNN [70]. The Faster-RCNN takes an image as input data and the output data is a proposal as a set of rectangular objects where every rectangle has an objectness score.
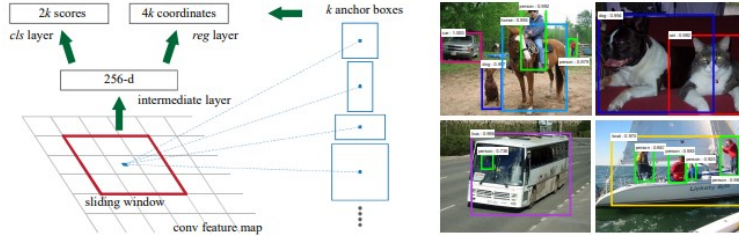

Figure 16: The left side shows a region proposal network which represents the Faster-RCNN network and the right side shows an example of the detection adapted from [70].

The attack is a Single Target attack where the label of the stop sign image changes to a speed-limit label, and a random target attack where the stop sign is randomly changed to an incorrect label. The results show a successful pass of the validation tests and 90% of the stop signs are missclassified as speed-limit signs. Gu et al. tested their ML model in a real-world attack by pasting a sticker on a stop sign near their office building. The ML model classified the stop sign with a 95% confidence as a speed-limit sign. The ML model's accuracy is decreased on backdoors to 1.3% which makes a misclassification to more than 98%. This attack is now transferred to the RMF for risk measurement to check how much the accuracy is reduced. The more the accuracy for the classification of the poisoned images is decreased, the higher is the possible extent of damage which increases the risk.

Clean Label Backdoor Attack In their work, Turner et al. [85] explain *Clean Label Backdoor Attack* attacks in direct comparison to Gu et al. *Pattern Backdoor Attack.* Turner et al. show an approach for executing backdoor attacks by utilizing adversarial examples and Generative Adversarial Network (GAN)-generated data. The approach of Turner et al. is analyzing the effectiveness of the attack of Gu et al. while a simple technique is applied for data filtering. Data filtering is a technique to find poisoned data by comparing the used training data with trusted training data. Turner et al. discovered that the poisoned inputs are outliers and are clearly wrong from the human inspection side. The attack would be ineffective if it would rely solely on poisoned inputs which are labeled correctly and evade such filtering. At this point Turner et al. created an approach that poisons inputs which appear plausible to humans. The inputs need small changes to make them harder while classifying them but the original label must still remain plausible. This transformation is performed by a GAN-based interpolation and adversarial bounded pertubations. GAN-based interpolation takes each input into the GAN latent space [28] and then interpolate poisoned samples to an incorrect class. Adversarial bounded pertubations use an optimization method to maximize the loss of

the pre-trained ML model on poisoned inputs while staying around the original input. The main focus of this attack are poisoned samples that still have poisoned labels. That is why the attack is called Clean Label attack which is originally from [78] in context of targeted poisoning attacks. Figure 17 shows an example airplane with different poisoned samples. The experiments base on the same patterns with a small black-and-white square in the bottom-right corner of the poisoned images as Gu et al. use in their work. The classifier is trained with the poisoned data and the test data are not labeled. The training dataset for the experiments is the CIFAR-10 dataset [45]. The ML model is a trained Wasserstein GAN [7], [32]. A GAN is strategy for training data where a game is defined between two competing networks. It contains a generator network and maps a noise source into the input space. A second network is the discriminator network which receives a generated sample or true data sample and then it must distinguish between those two samples. The Wasserstein GAN is using the Earth-Mover distance which is also called Wasserstein-1. For further explanation of the mathematical structure, please see [33].

Figure 17: Difference between an original image and the conversion into adversarial examples with different pertubations adapted from [85].

Hidden Trigger Backdoor Attack The last backdoor attack from Saha et al. [72] is the *Hidden Trigger Backdoor Attack* which goal is to let poisoned data look natural with correct labels. This backdoor attack uses a threat model defined from Gu et al. [31]. In this threat model, the attacker provides poisoned training data to a victim that uses it with a pre-trained ML model. The attacker uses a small image as a backdoor which changes the target label to a specific wrong label. This can be used for both attack specificity, targeted and untargeted. With this threat model it is possible to identify the poisoned data because as already explained in *Clean Label Backdoor Attack*, the missclassified images change their label. Identifying the poisoned data in a training set can show how many images are poisoned to measure the extent of possible damage. Saha et al. propose a threat model inspired from Shafahi et al. [78] and Sabour et al. [71] where the poisoned data are labeled correctly and the backdoor also remains not visible. This is done through optimization for poisoned images which pixel space is close to images from a target category while its feature space is close to source images that are patched with the backdoor. The next part is generalizing the attack for unseen source images which means that the trigger cannot be found during poisoning. Also the trigger should

be placed at any random location. In order to implement this, during the optimization the poisoned images pushed close to a cluster of source images that are patched. Based on the work of Moosavi-Dezfooli et al. [**?**] about universal adversarial examples, Saha et al. minimized the value of loss at all source images and trigger locations. This is done by choosing a random trigger location and source images for each iteration of optimization. Over every iteration a method optimizes randomly patched source images and assigns them to poisoned images closest to the feature space.
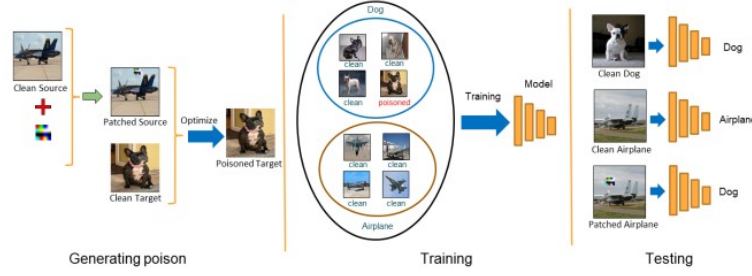

Figure 18: The left side visualize how an attacker generates a set of poisoned images. In the middle the visualization shows how the training data is extended by the poisoned data and then the victim trains the ML model. The right side visualize the test time. An attacker adds the backdoor trigger to images with the source category to manipulate the ML model without changing the label. This visualization is adapted from [72].

3.6. Measurement method for the extent of damage

Based on the attacks, this subsection explains how the extent of damage is measured. As the hypotheses H1 assumes, the attack specificity, attack time, and the TP, TN, FP, FN are risk indicators. Based on [31], [85], and [72], the accuracy metric of a ML model for a specific image is a value that represents the success of a backdoor attack. All of these risk indicators are assigned with values before and after an attack during the training of a ML model. These data can be collected directly from the ML model which represents the low-level attributes in the threat model from Doynikova et al. [22]. To get these assigned data the RMF needs a measurement method based on the low-level attributes. The attack time and attack specificity are both mapped to the high level attributes as Figure 23 shows. After the training the RMF assigns the values of the risk indicators to the base measures which is the conclusion of the measurement methods.

3.7. Measurement method for the attacker's effort

After explaining the procedure to get the base measures to measure the extent of damage, this subsection explains how the base measures for the attacker's effort are measured. Breier et al. [18] propose the attacker's knowledge and goal. Further, theses proposals and the computational resources as hypotheses H2 describe are used as the risk indicators.

| Clean target | Clean source | Patched source | Poisoned target |
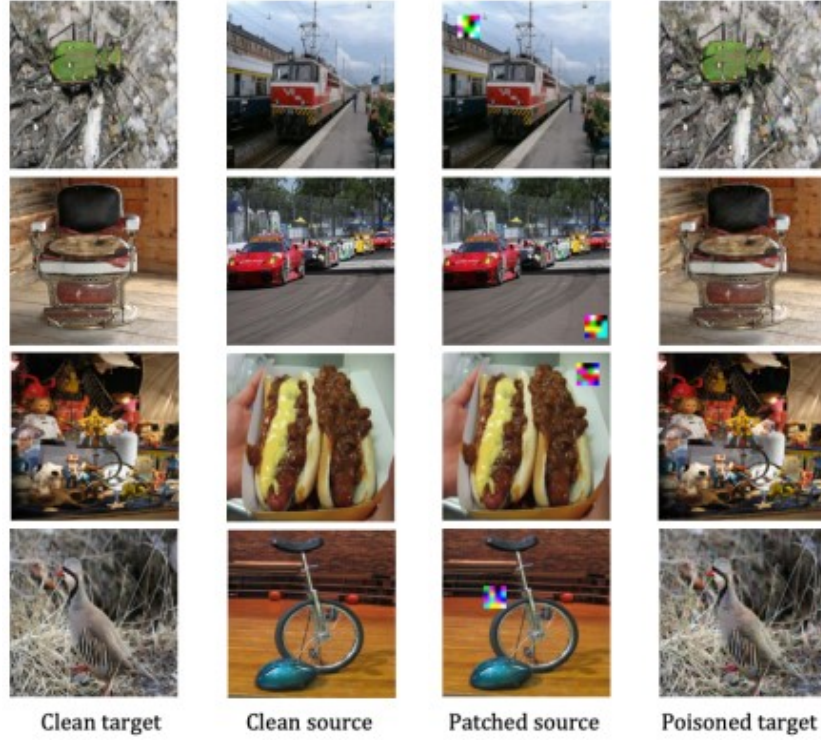
Figure 19: The left side visualize how an attacker generates a set of poisoned images. In the middle the visualization shows how the training data is extended by the poisoned data and then the victim trains the ML model. The right side visualize the test time. An attacker adds the backdoor trigger to images with the source category to manipulate the ML model without changing the label. This visualization is adapted from [72].
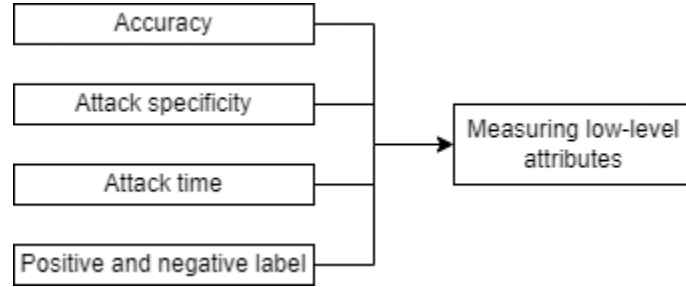
Figure 20: Risk indicators of the attack object in relation to the low-level attributes measurement method.

Starting with computational resources that are a need to train a ML model. This riks indicator gets the current use of the central processing unit (CPU), graphics processing unit (GPU), and memory resources to find out what an attacker needs to test and execute his attack. The attacker's knowledge is divided into two possible knowledge levels. The first knowledge level are black-box attacks where the attacker has no information about

the ML model.

In their work, Papernot et al. [65] explain a black-box attack strategy to misclassify a deep neural network (DNN) [3] by generated adversarial examples. Papernot et al. assume that the attacker has no knowledge about the structure, parameters, and does not have access to any training set that this DNN uses. The attack strategy has no need to train an independent training dataset. The goal is to train a DNN with synthetic input data and generated from the adversary. Synthetic datasets are reflecting real datasets by preserving their relations between the variables and statistical properties [69]. The output data are assigned labels from the targeted DNN and the adversary observe the output data. The input data are handwritten digits as images and the output data are one of these digits. The aim of the attack is to get a minimal altered version of each input which is called an adversarial example. This should misclassify the input data by a minimal pertubation. This happens by generating the synthetic dataset which the adversary generates.

The second knowledge level are white-box attacks where an attacker has nearly perfect knowledge about the ML model. Prinz and Flexer [68] present end-to-end adversarial attacks on classifications of music instruments. The training data are from the DCASE2019 Challenge [23]. In their work, Prinz and Flexer use four adversarial white-box attacks. Two attacks are untargeted and called Fast Gradient Sign Method (FGSM) [29] and Projected Gradient Descent on the negative loss function (PGDn) [54]. The other two targeted attacks are adaptions from the Carlini and Wagner (C&W) [19] method. The architecture is a convolutional neural network (CNN) [44] as Figure 21 shows.
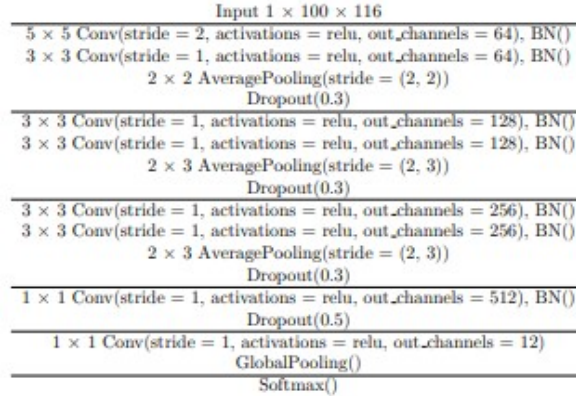


```
                    Input 1 × 100 × 116
5 × 5 Conv(stride = 2, activations = relu, out_channels = 64), BN()
3 × 3 Conv(stride = 1, activations = relu, out_channels = 64), BN()
              2 × 2 AveragePooling(stride = (2, 2))
                         Dropout(0.3)
3 × 3 Conv(stride = 1, activations = relu, out_channels = 128), BN()
3 × 3 Conv(stride = 1, activations = relu, out_channels = 128), BN()
              2 × 3 AveragePooling(stride = (2, 3))
                         Dropout(0.3)
3 × 3 Conv(stride = 1, activations = relu, out_channels = 256), BN()
3 × 3 Conv(stride = 1, activations = relu, out_channels = 256), BN()
              2 × 3 AveragePooling(stride = (2, 3))
                         Dropout(0.3)
1 × 1 Conv(stride = 1, activations = relu, out_channels = 512), BN()
                         Dropout(0.5)
   1 × 1 Conv(stride = 1, activations = relu, out_channels = 12)
                        GlobalPooling()
                          Softmax()
```

Figure 21: The neworks contains $5x5$ and $3x3$ convolutional layers with the ReLU activation, batch normalisation, and average-pooling layers. The CNN uses dropout for regularisation and the final layer is a $1x1$ convolutional layer adapted from [68].

PGDn is an attack on a negative loss function [53] which goal is increasing on a sample the negative loss interatively. FGSM is a method which goal is to increase the loss by moving a scaled step in gradient direction while the adversarial pertubation is computed [29]. C&W's first method is about using gradient descent to minimise the loss to a specific class. The Multi-Scale C&W attack keeps pertubations small with the squared norm [19].

Prinz and Flexer [68] and Papernot et al. [65] show both ways to attack ML models and in both works they used specific attacks for specific ML models. Both attacks bases on white-box or black-box attacks which shows that it is possible to find out if an attack is a black- or white-box attack. And after that is found out it should be possible measure the knowledge by pre-determined steps to execute the attack [26]. To measure the attacker's knowledge for black- and white-box attacks, the explained attacks in 3.4 should represent these attacks. *Hidden Trigger Backdoor Attack* [72] is an attack where the attacker uses a backdoor trigger on a pre-trained ML model with finetuning for classification. The backdoor trigger must be implemented while finetuning the ML model to change the label. When the ML model finetunes its training data, the attacker changes the source label to a target label. *Clean Label Backdoor Attack* [85] is an attack which misclassifys instead of inference, during training time. With this goal, the images should be harder to be correct classified and the ML model should recognize the backdoor trigger as a feature. That should prevent modificatons during training time of the poisoned data. This attack is implemented based on projected gradient descent (PGD) [53]. PGD is an approach to train NN with a improved resistance against adversarial attacks. *Pattern Backdoor Attack* [31] is an attack which adds a pixel pattern or single pixel into an image and misclassifies these poisoned images to a target or untargeted label. After adding the pattern these poisoned images have to be mixed back into the original training dataset. The attacker's goal is the last risk indicator to measure the attacker's effort to find out what the attacker is trying to achieve [18]. To find this goal in the measurement method, this risk indicator has to know which attack is used. If this attack clarified, the goal is to measure pre-determined steps. Then the risk indicator can calculate the highest probability on pre-defined goals. The pre-determined steps in the attacker's knowledge and goal are also affected from the low-level attributes which Figure 23 shows. When all risk indicators are assigned with its values then the measurement methods can pass all results to the base measures.
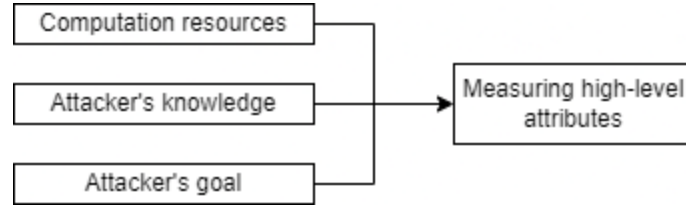

Figure 22: Risk indicators of the attacker object in relation to the high-level attributes measurement method.

3.8. Using the formal threat model

To measure the extent of damage, subsection 3.6 describe which risk indicators the RMF uses to get the corresponding values. As already explained in subsection 3.6, these values must be collected from the measurement method of the low-level attributes which explains this subsection how this works. After that, subsection 3.7 explains how to get the

corresponding values for the attacker's effort. The concept to measure the corresponding values that are assigned to the risk indicators describe subsection 3.7 and is further explained here by the threat model. In this subsection the research questions RQ2 and RQ3 are addressed in more detail. In reference to the research question RQ4 this threat model is a possible method for the RMF to measure risks which will be proved in section 5. As in section 2.3 explained, the high- and low-level attributes have to be mapped which this subsection also explains.

Before explaining the procedure there are two requirements for the dataset that is collected from the attributes [22] for the analysis process. These requirements are already transferred to ML models:

1. The first requirement is a dataset which contains information about the attack actions against a ML model. The information must be based on the skills, resources, intention, and motivation of the attacker.

2. The second requirment for the dataset is that everything is marked in such a way that the analysis shows which actions the attacker performed. But this requirement is more about having multiple attackers or the analysis accross multiple attackers.

The second requirement can not be fulfilled because this thesis do not differentiate between one or multiple attacker. It is only ever one attacker.

The low-level attributes

To find the extent of damage there is a need to collect data which can be measured from every attack on a ML model. These data are classified and explained in section 2.3. Doynikova et al. [22] explain which data are required to meausre the low-level attributes. The low-level attributes that Doynikova et al. use in their work are event logs, network traffic, namely, and their source that are possible to use in relation with the risk indicators. A possibilty for this is monitoring the values for the risk indicators with event logs, namely, and their source. The network traffic can not be used because the RMF only measures an attack on a ML model locally what does not include MLaaS [34]. The low-level attributes measure the extent of damage based on the collected data. It is therefore important that data about the ML model and the attack can be collected during the entire training and testing process. For example, if the attack specificity needs to be measured then it must be possible to get this through the attack itself. After the assignment of the values Doynikova et al. explain that the low-level attributes must be mapped to the high-level attributes to measure the attacker's effort. The high-level attributes have delimited attributes which are not measured at the low-level attributes. This means the attributes must be evaluated in a separate measurement method afterwards.

The high-level attributes

The high-level attributes measure the values for the attacker's effort based on the risk indicators attacker's knowledge, attacker's goal, and the computational resources. The

four groups explained in subsection 2.3 are placed in relation to the risk indicators. The first group includes characteristics such as skills, motivation and intention. The motivation and intention correspond to the attacker's goal. The skills are a characteristic that are represented in the knowledge and goal. The second group characterizes the attacker's capabilities [91] and show the characteristics as used resources. This group represents the computational resources. This risk indicators measures which hardware an attacker needs to execute an attack. The third group incorporates the attacker in relation with the attacked system. This group includes the attacker's location, the privileges, his goals, the access and the attacker's knowledge. This part can be used for the RMF with the attacker's goals and knowledge. The attacker's location and privileges are not part of the risk measurement. The last group relates the attacker with the attack and the steps that are included to execute the attack. This group can be used to map the low- and high-level attributes what is explained next.

Mapping the low-level with the high-level attributes

After explaining the low- and high-level attributes as separated measurement methods, the low- and high-level attributes must be mapped based on the threat model of Doynikova et al. [22]. At this point, the attacks are displayed on the basis of their values. At the beginning, the data of the attacks are measured separately in the measurement method of the low-level attributes and then those of the high-level attributes. The data here always refer to the risk indicators before and after an attack to monitor the original and the manipulated training dataset. Starting with the measurement of the low-level attributes the accuracy and TP, TN, FP, and FN. These risk indicators can be only used to find the extent of damage. The attack time and specificity is relevant for the extent of damage and to find the attacker's effort. This risk indicator gets values that can be transferred to the risk indicators attacker's knowledge and goal. The computational resources are a risk indicator that is only for finding the attacker's effort. Figure 23 summarize this mapping and and in comparison to the threat model of Doynikova et al., the values are completely collected and evaluated without human judgment.
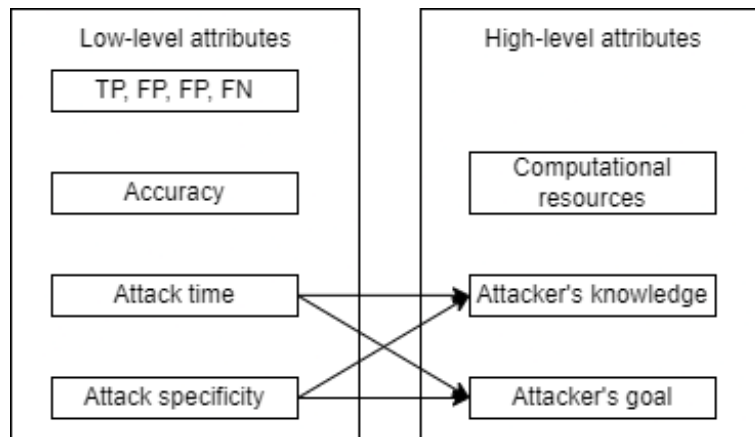

Figure 23: Mapping between the low- and high-level attributes.

3.9. Define measurement functions to calculate derived measures

In this subsection the base measures are also called risk indicators because the RMF shows the output of the measurement methods assigned to the respective risk indicator. Not every derived measure need to be calculated such as the accuracy and computational resources. The TP, TN, FP, and FN are a risk indicator that can be calculated in a measurement function to different ML metrics such as the accuracy [57], confusion matrix [90], precision-recall [21], and F1-Score [57] which subsection 2.4 describe. This metrics are used to show the differences between an original and poisoned ML model. The derived measures that represent values of the ML model are only calculated from one risk indicator because this risk indicator have multiple different values that are needed to calculate the ML metrics.

The risk indicators which are combined to derived measures shows Figure 24. The first derived measure resulting from all values that describe the attack and how and where to execute it. If all of them are combined, then should the derived measure be a value that represents without the computational resources how high the effort is to implement, test, and execute an attack.

The combination starts by the attack time and specificity where the attack is executed during training or testing time. If the attack is, for example, executed during testing time, then the concentration is located on all steps after the training of the ML model. If the attack specificity is, for example, untargeted then the attacker can poison the training dataset without finding out label names and only have to add a backdoor trigger. When the attacker decide to implement a backdoor attack then he have to go through pre-determined steps which are defined depending on the used attack. The same applies to the goal which bases on pre-determined steps too. With these information is it possible to combine them and then getting the derived measure. The same procedure combine the measurement function for the extent of damage from the attack time and specificity. The accuracy and computational resources are not considered further here because they are transferred directly to the analytical model.

3.10. Define analytical models and indicators

The indicators are the final results from the measurement and provide the transition over the decision criteria to the measurement results. After evaluating the derived measures, all measures have to be combined for calculating all values to get the extent of damage and attacker's effort. To get both values, the RMF need to combine the base and derived measures depending on the target value which Figure 25 shows. So, the result is, that for this thesis the RMF needs two indicators. Depending on that requirement there have to be two analytical models [2]. The analytical models get at this point the function to calculate the measures for the interpretation in the decision criteria. This differentiate from the requirements of analytical models of ISO 27004 [2] but is necessary for the risk result which subsection 3.11 explains.
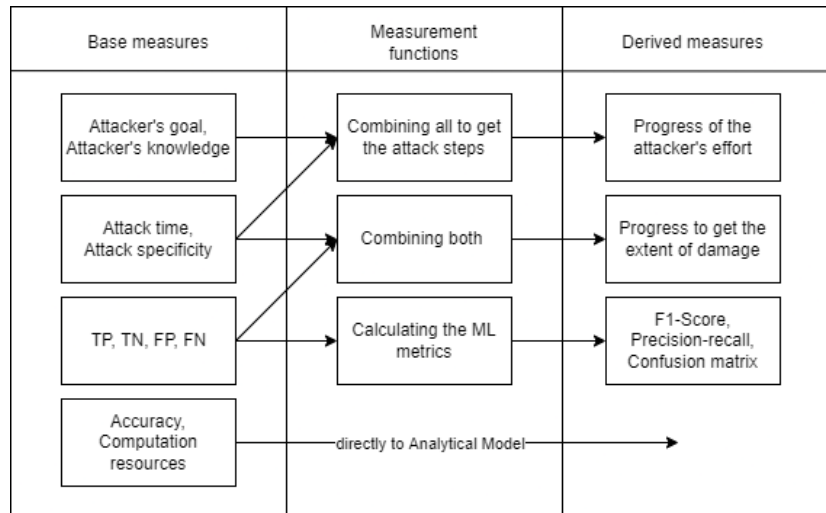
Figure 24: Combine the risk indicators to derived measure and evaluate the derived and base measures with the analytical models to indicators.
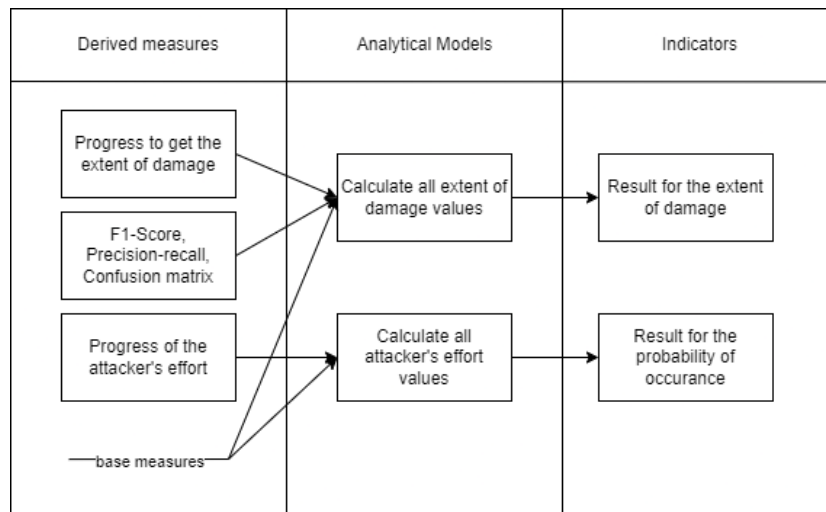

Figure 25: Calculation of the derived and base measures in the analytical models to get the indicators.

The transition between measurement and measurement results

After defining the indicators the next step is the transition to the measurement results by interpreting the indicators based on decision criteria. At this position it is important to relate the attacker's effort with the probability of occurrence because this values is used to get the final risk value.

The goal for the decision criteria is to interpret the indicators without human judgment. Based on this the functionality of the decision criteria should decide on given intervals how the indicators can be interpreted.
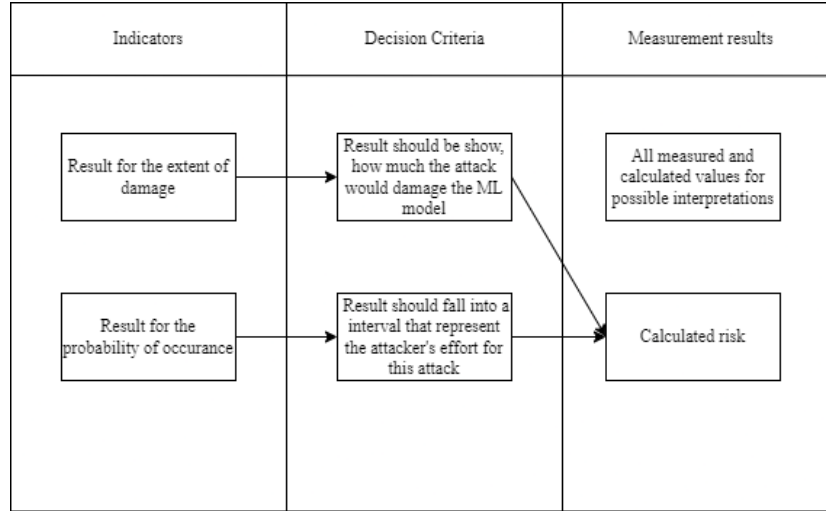
Figure 26: Interpreted results that should contain requirements which specify the decision criteria.

3.11. Develop measurement results by evaluating the risk measurement

The implementation of the measurement results are possible through the decision criteria which are also defined in [2]. The RMF show the results as visualized Python plots and calculated results. Both bases on the risk indicators.

Machine learning metrics for risk measurement

With regard to poisoning attacks, the goal is to decrease the accuracy [16], [31]. But the RMF should also use the precision-recall, the F1-score and shows learning curve of the training process. That should make it possible to identify everything of the attacks. Also with regard to the attacker's effort could be every collected information of the ML model and the training data a possible value.

Calculate the risks

The main calculation is *Risk = Extent of damage * Probability of occurrence* [40]. This calculation is intended to show how high the risk is for an ML model. Other calculations are to be displayed in detail as probabilities and stand in relation to the extent of damage or probability of occurance. For example, the composition of the extent of damage from the various risk indicators can be presented again in detail. This risk calculation is classified in a matrix for the extent of damage, a matrix for the attacker's effort, and a matrix that summarizes these matrices by classifying the calculated risk. Figure 27 shows a sample matrix where green is the lowest risk level and red the highest. The *x-axis* and *y-axis* show different combinations to classify the values that classify the risk value into the risk matrix.
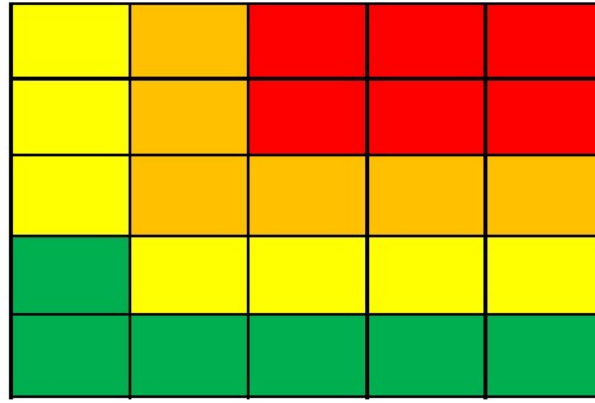
38

Figure 27: Sample risk matrix adapted from [38].

This classification bases on the European Telecommunication Standards Institute (ETSI). In their standard [74] ETSI show a risk classification standard which table 1 shows.

Risk	Explanation
Minor	"No essential assets are concerned, or the attack is unlikely. Threats causing minor risks have no primary need for counter measures."
Major	"Threats on relevant assets are likely to occur although their impact is unlikely to be fatal. Major risks should be handled seriously and should be minimized by the appropriate use of countermeasures."
Critical	"The primary interests of the providers and/or subscribers are threatened and the effort required from a potential attacker's to implement the threat(s) is not high. Critical risks should be minimized with highest priority."

Table 1: Risk classification adapted from [74]

3.12. The implementation plan of the RMF

The last point (g) - "Establishing measurement implementation approach and documentation" of 3.1 shows the needed information for an implementation plan. This subsection shows the final concept as a complete structure. At first a classifier check the trustworthiness of the training data by comparing the training data with trusted training data. To measure the extent of damage there need of an implementation of the low-level attributes. To get the attacker's effort another measurement method should represent the measurement of the high-level attributes. These two classes need to be mapped.

The final concept and design for the RMF

After explaining the expected results the last part of this section shows the summarized concept and design to implement the RMF in the following section. Table 2 and 3 show the two objects with its attributes that represent the risk indicators for the measurement methods afterwards.

Attack object	
Attributes	**Description**
Accuracy	The accuracy relates the number of data examples with true predicted labels to the number of all examined data examples [57].
TP, FP, TN, FN	
Attack specificity	The attack specificity can be targeted or untargeted
Attack time	The attack time differentiate between training and deployment time

Table 2: ISO 27004 Object (attack)

Attacker object	
Attributes	**Description**
Attacker's goal	The attacker's goal can be a denial-of-service, doing an inference failure, or obtaining secret information
Attacker's knowledge	The knowledge of an attacker can be categoraized between white-, black-, or grey-box
Computational resources	The CPU, memory, GPU are the three parts which represent the used effort from the computer to attack and train a ML model.

Table 3: ISO 27004 Object (attacker)

In Figure 28 the identified risk indicators are passed to the measurement methods which are one of the two main components for the risk measurement. As next must the backdoor attacks selected to measure the value that are assigned for the next main component, the measurement which follows the requirements from ISO 27004 [2].

3.13. Expected results of the RMF

After attacking a ML model without considering the defense, the values of the accuracy of the poisoned data should be lowest value (%) as possible which is the highest effectiveness of the attack. The accuracy of the original training and testing should be completely unchanged or so minimally changed that it is not noticeable. The attack time should always recognize that the attack is executed during training time because all attacks in
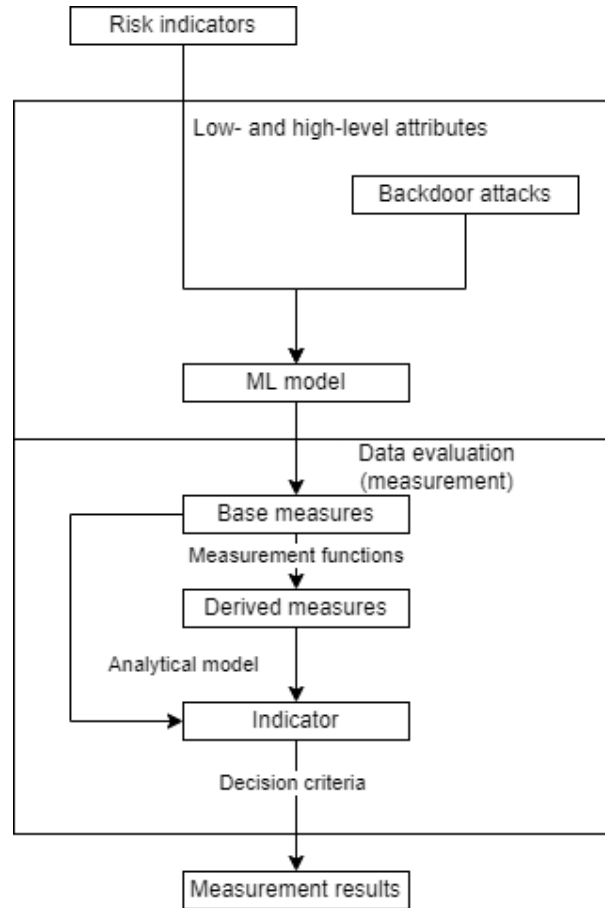
Figure 28: Complete concept architecture adapted from [2].

this thesis are backdoor attacks. Attack specificity should be always find if an attack is targeted or untargeted if the attacker whether the attacker specifies a target or not. Attacker's goal should reproduce the steps of an attacker based on the attack to find the goal of that attack. Attacker's knowledge should measure the attacks depending if it is a white- or black-box attack, which attack time, and attack specificity is measured before. The risk result of the risk measurement without any defenses of the ML model should be the worst possible risk level in the risk matrix.

4. Implementation

Afer explaining and discussing the concept this section describe the implementation of the technical framework RMF by following the procedures of ISO 27004 [2]. The technical RMF uses Python 3.7 as the programming language and ART as the basis. Beside the attacks given by the ART, there is a function from the technical RMF to execute individual attacks. This technical RMF should be used a step ahead of using the framework of Schwerdtner et al.

4.1. Structure of the RMF

Directory tree

The RMF is structured as follows:

```
rmf/
├── attacks/
│   └── art/
│       └── backdoors.py
├── backdoors/
│   └── png-Files
├── measurement/
│   └── monitoring.py
├── metrics/
│   └── log.py
├── visualizations/
│   └── plot.py
├── log_file.log
└── case_study.py
```

The *png-Files* are used by the *backdoors.py* script to add patterns into the images that are the backdoor triggers. Both folders *measurement* and *metrics* contain implementations to monitor the collected data for the risk measurement and evaluate it. The *visualizations* folder shows the measurement results and summarize them into one output file.

4.2. Implementing the risk indicatiors

The risk indicators are the main part for the risk measurement. Therefore the risk indicators are used through the complete risk measurement. Every risk indicator is implemented as an own function in the RMF. This makes it possible to measure the risk indicator values at every step during the ML model training. The goal is to use measure the risk indicator values with the original training data and the manipulated training data. The $accuracy = \frac{n(correctly\_predicted)}{n(all)}$ is implemented as Nguyen and Zeigermann [57] describe it. The next risk indicator is the attack time that checks when the attack execute. This can be during training or deployment time. Implementing this checks which attack is executed. Attack specificity is an risk indicator that measures if the attack is targeted or untargeted. This is a risk indicator that measures where the backdoor trigger is implemented. The ART attacks have a parameter that takes target. If the target is random, there is no specific label. If it is targeted, there is a specific label where a certain number of images in percentage are poisoned or specific images of a targeted label. Positive and negative label is a risk indicator that measures during training time the TP, TN, FP, FN. Keras show these values with a implemented function in this technical framework. The computational resources get the values from the operating system for the specific executed program. The attacker's knowledge is implemented based on the attack. For example, if the *Pattern Backdoor Attack* is implemented in the ML model, then the function for the attacker's knowledge returns the steps to implement this specific attack [26]. Attacker's goal [18] can be an inference failure, obtain secret information, or executing a denial-of- service. The goal of this risk indicator is to evaluate it based on monitored data of the attack. So the attack must have characteristics that represent the goal an attacker has. An inference failure happens during the testing phase. So when an attacker try to execute an inference failure he could use exploratory attacks [83]. Obtain secret information can be for example stealing model attacks [88], [93]. Denial-of-service attacks have the goal to slow down the ML model or crash the ML model completly [86].

4.3. Implementing backdoor attacks from the ART

The following three attacks are all based on the ART [60] and represent white-box and black-box attacks and both targeted and untargeted attacks. These attacks are the main factor to assign the values to the base measures. The attacks already differentiate between the original and poisoned dataset for evaluation.

Backdoor attacks from the ART

All backdoor attacks use the *Pattern Backdoor Attack* [31] class which expects a pattern argument. The pattern is a picture which is for the poisoned images in the training data. The pattern must be implemented before training and choose a random selection of images. This is implemented in the RMF as follows:

```
1  n_train = np.shape(x)[0]
2  num_selection = num_of_rand_images
3  random_selection = np.random.choice(n_train, num_selection)
4  x = x[random_selection]
5  y = y[random_selection]
```

Then the arguments x and y are passed to the poisoning function from the ART. x and y are parameters which the function expects when calling it. Appendix A describe the functions and parameters. Further it is important that the shape of the images from the training data are *N, H, W, C* or *N, C, H, W*. *N* is the number of images in the batch, *H* is the image height, *W* is the image width, and *C* is the channel number of an image such as grayscale or RGB. After adding a backdoor as a pattern to the random images, the poisoned images are replaced back to the training data. These poisoned images are saved in a different folder to check if the images are missclassified after or while testing the ML model.

The first attack uses the *Pattern Backdoor Attack* class without any other backdoor classes from the ART. This attack which bases on Gu et al. [**?**] is a black-box attack which is untargeted. In the RMF it uses a pattern backdoor which Figure 29 and Figure 30 show as the difference between the original and the poisoned image. The goal of this attack is to change the original label to a random other label. This attack can be executed without any information because it is not important which training data the ML model use and what ML model is used for the training itself.

After poisoning the images these image need be copied back into the original training data. Before this can be done the poisoned data must replace the original training data which contain no backdoor. When the RMF take the random original images, it save them into a temporary variable and then delete the images from the original training data. The next step is the poisoning while the poisoned data and the original training data need the same shape and dimension which make it possible to copy the poisoned images. As mentioned before the poisoning function takes only two specific shapes which make it easy to have the same shape in the original training data and poisoned data. The implementation of the attack additionally shows the effort an attacker have to implement this attack. Thus the steps can be used for the attacker's knowledge risk indicator.

The *Clean Label Backdoor Attack* [85] poison images and misclassify during the training time. To use this attack the *Pattern Backdoor Attack* must be used before and then the clean label attack can be executed after training. After adding the backdoor trigger with *Pattern Backdoor Attack* the original training data are trained with a proxy classifier which should do the same classification tasks as the original classifier. The first poison step is selecting target images. As next the PGD (which is untargeted) must be implemented to make it harder classify correctly. The last step is adding the backdoor trigger and add
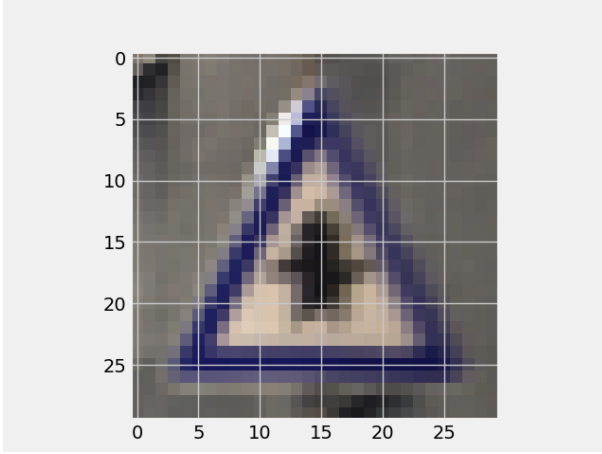
Figure 29: Street sign without a backdoor pattern with the label *Right-of-way at intersection*
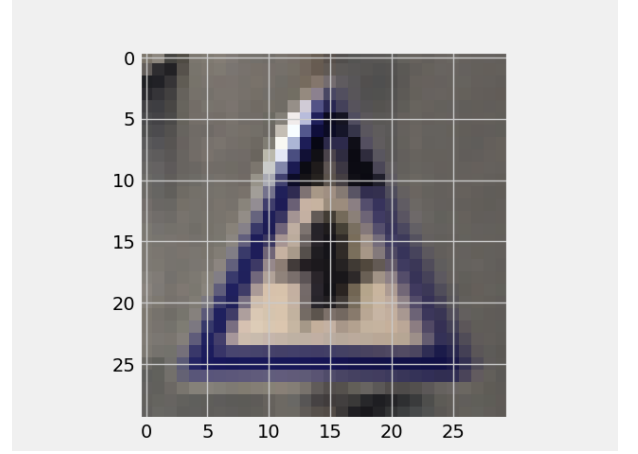

Figure 30: Street sign with a backdoor pattern but still with the original label *Right-of-way at intersection*

the target label.

The *Hidden Trigger Backdoor Attack* [72] need to be executed after training. To add the backdoor, the *Pattern Backdoor Attack* must be used before. After training, the poisoned data and a smaller number of clean training inputs are used to finetune the model. Finetuning means, adjusting parameters of the ML model to improve it with a small amount of training data to improve the performance [49], [20]. For the attack the poisoned data are used with a small amount of clean training data. The following Python code shows the finetuning of a ML model where the attack is implemented.

```python
dataset_size = size
num_labels = label_size
num_per_label = dataset_size/num_labels

poison_dataset_inds = []

for i in range(num_labels):
    label_inds = np.where(np.argmax(y_train, axis=1) == i)[0]
    num_select = int(num_per_label)
    if np.argmax(target) == i:
        num_select = int(num_select - min(num_per_label, len(
  poison_data)))
        poison_dataset_inds.append(poison_indices)

    if num_select != 0:
        poison_dataset_inds.append(np.random.choice(label_inds,
  num_select, replace=False))

poison_dataset_inds = np.concatenate(poison_dataset_inds)
```

```
19    poison_x = np.copy(x_train)
20    poison_x[poison_indices] = poison_data
21    poison_x = poison_x[poison_dataset_inds]
22
23    poison_y = np.copy(y_train)[poison_dataset_inds]
```

The implementation of the *Hidden Trigger Backdoor Attack* is analogous to the *Clean Label Backdoor Attack* but it takes a different pattern as the backdoor trigger which Figure 19 shows.
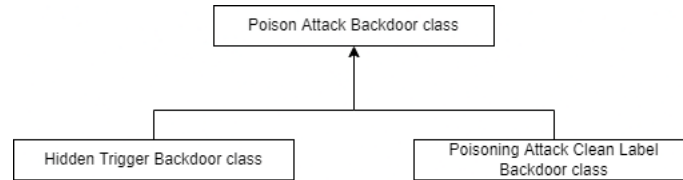

Figure 31: Both attack classes (*Clean Label Backdoor Attack* and *Hidden Trigger Backdoor Attack*) get the backdoor from the *Pattern Backdoor Attack*

4.4. The logging function

Assigned values of the risk indicators are represented with an optimized logging function, based on the Python logging module. The function waits for two parameters. A message string and the wanted logging level (i.e. INFO or DEBUG). The called log function in the RMF could look like this:

```
1    log(f"{variable_name}", 'INFO')
```

In order not to depend on the different ML libraries the rmf gets its own functions of the different metrics. That increases the support of different Python libraries for ML risk measurement.

4.5. Using the threat model

The measurement methods are implemented based on the threat model of Doynikova et al. [22].

4.6. Evaluation with the measurement construct of ISO 27004

After assigning the risk indicators based on the threat model of Doynikova et al. [22], this subsection explains the implemented measurement construct starting from the base measures up to the decision criteria.

4.7. Show the measurement results

The measurement results show the monitored data based on the measurement process of ISO 27004 [2]. This contains all logged risk indicator values and ML metrics. A second part shows the risk for the ML model with an attack. The risk is calculated by $Risk = Extent\ of\ damage * Probability\ of\ occurence$. The result of this is classified in the risk matrix. The complete measurement results shows appendix C. The following section evaluates the RMF risk measurement based on a case study which contains the street sign classification on autonomous driving which is attacked by different backdoor attacks.

5. Evaluation

A common example to show backdoor attacks is traffic sign detection ([58], [31], [62], [48]). That makes it easier to find datasets and already finished ML models to make a case study. In the following subsections the focus lies on the case study which concept and its implementation is evaluated here. In addition, this section describes real-world examples for which the RMF could be used.

5.1. Evaluation of the ISO 27004 standard in context to the RMF

After mapping the ISO 27004 to the RMF one result is that this standard should be mapped to a framework if the process stands in relation to a organization and an implemented ISMS.

5.2. Case Study: Developing a SVM for traffic sign detection

For the case study scikit-learn [66] and for preparation of the dataset in Python OpenCV2 have different function to load and resize images [17]. In their work, Stallkamp et al. [82] built a mulit-category classification dataset. The mulit-category classification dataset contains german traffic signs for image classification. That mulit-category classification dataset uses the german traffic signs from a approx. 10 hours daytime video from different roads. This case study is an example to show the functions and results of the RMF. After showing this case study there will be explain and discuss realistic case studies where backdoor attacks could have a more realistic impact for scores of ML models.

5.3. Structure of the ML model for the case study

The original dataset from Stallkamp et al. [82] is splitted between a training and testing folder. The training folder separate 43 signs into subfolders. This subfolders make it easy to use specific traffic signs which decrease the training time. The information of the folders are written in an eponymous csv-file that are not needed further in this case study. In Figure 32 the shown traffic signs can be used for training the SVM and are all labeled in the data preprocessing like the subfolder name 0 - 42.
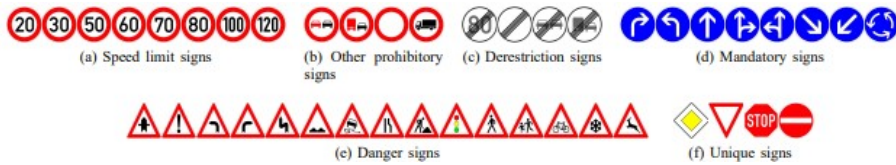

Figure 32: Labeled traffic signs adapted from [82]

All signs are resized to 30x30 pixel to optimize the performance of the NN. The training sets are also scaled with Keras and TensorFlow to execute the attacks successfully. The training data and test data load from two different folders. All functions, the arguments
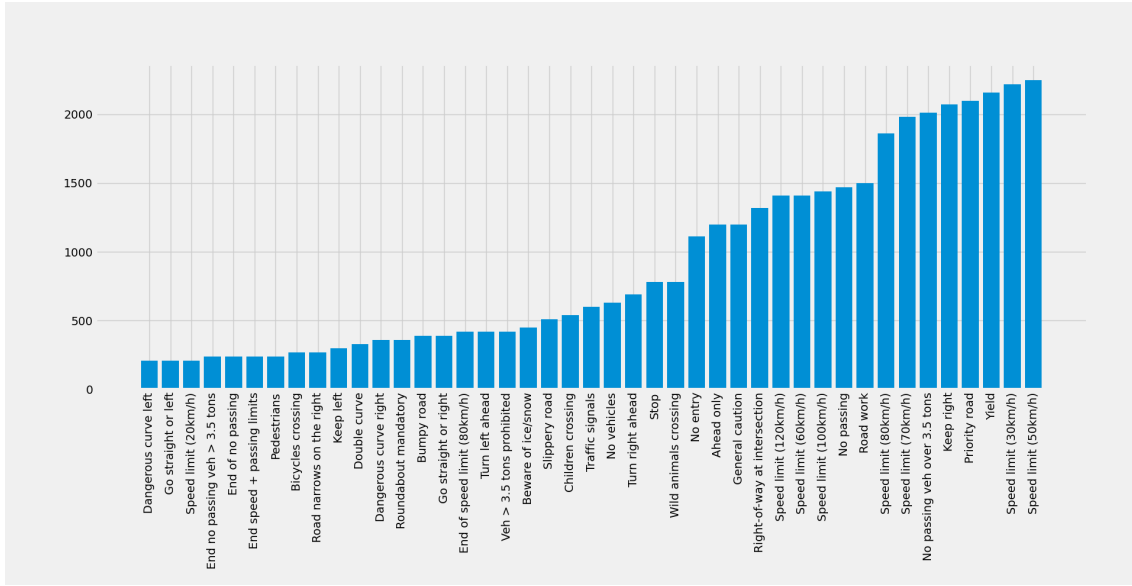
Figure 33: Number of images per labels

and a description of them can be found in appendix B. Figure 34 shows the NN architecture.

The computer to execute the ML model have resources such as, AMD Ryzen [8] 7 5800X 8-Core Processor with 3.80 GHz, 16 GB of RAM, and a NVIDIA GeForce RTX [73] 3060 Ti. These resources can be used for the risk indicator computational resources to measure the original and attacked ML model.

Expected results of the case study

5.4. Differences between manipulated and original dataset

The Python plots from the case study show in this subsection examples images to show the differences between the original and manipulated dataset.

5.5. Results from the risk measurement based on the risk indicators

Risk indicators to measure the attacker's effort

Attacker's goal
Attacker's knowledge
Computational resources The computational resources that are measured are the CPU, GPU, and RAM. The RAM measurement starts at the beginning of the implemented ML model and shows after finishing the training and testing time of the ML model how much RAM resources the ML model used. When the ML model has no attacks implemented, the ML model needs %

49
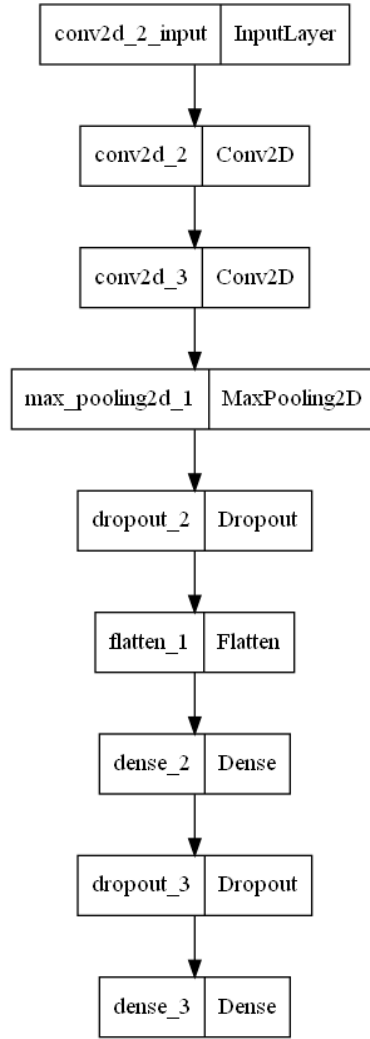
Figure 34: Generated NN architecture image from Keras

Risk indicators to measure the extent of damage

Attack time All backdoor attacks are executing during training time.
Positiv and negative label
Accuracy The accuracy is a risk indicator should be decreased as much as possible if an ML model is attacked with a backdoor attack. The original ML model has an accuracy of 96%
Attack specificity The *PoisoningAttackBackdoor* is a untargeted attack, *PoisoningAttackCleanLabelBackdoor* is a targeted attack, and the *HiddenTriggerBackdoor* is a targeted attack.

5.6. Poisoning and backdoor attacks in real applications

Beside the exemplary application from the case study, the scientific papers in this subsection show real applications where the RMF can then help in a more real environment. An example for real-world poisoning attacks against ML models is Microsoft's chatbot Tay. This chatbot learned racist and offensive language from Twitter users [13], [12]. Microsoft removed the bot after 16 hours because the bot produced offensive tweets.

6. Conclusion

This section summarizes this thesis, discusses the results related to the goals, research questions, and hypotheses from section 1. Furthermore, this section explain a possible future work based on the concept, implementation, and evaluation of the current state of the RMF.

6.1. Discussion of the results

The ISO 27004 standard is very generalized. That makes it possible to design and implement frameworks which are not covered as a standard or intended to be.

6.2. Future work

The attack object should be splitted into different attack techniques because every attack technique has its own characteristics and different goals to achieve with it.

A. Framework functions

```
1   log(message, logging_levelname: str = 'INFO')
```

message output in the log

logging_levelname (Optional) string value to show the logging level

The following functions are the attacks in the RMF:

```
1   art_poison_backdoor_attack(x, y, num_of_rand_images)
```

x This argument takes the array of training images.

y This argument takes the array of labels that are assigned to the training images.

num_of_rand_images This argument takes the number of untargeted images that should get a trigger pattern.

```
1   clean_label(x, y)
```

x This argument...

y This argument...

```
1   art_hidden_trigger_backdoor(x, y, target, source)
```

x This argument...

y This argument...

target This argument...

source This argument...

The following functions visualize the ML model training process:

```
1   create_learning_curve(est, x_train, y_train, train_sz)
```

est This argument...

x_train This argument...

y_train This argument...

train_sz This argument...

```
1   make_meshgrid(x, y, h=0.02)
```
x Data to base x-axis meshgrid on

y Data to base y-axis meshgrid on

h (Optional) stepsize for meshgrid

```
1   plot_contours(ax, clf, xx, yy, **params)
```
ax Matplotlib axes object

clf Classifier

xx Meshgrid ndarray

yy Meshgrid ndarray

**params (Optional) dictionary of params to pass to contourf

The following functions show the data results of the risk measurement:

```
1   probability_calculation()
```

```
1   list_probability()
```
The following functions represent the risk indicators in the RMF:
These three functions form the computational resources risk indicator:

```
1   ram_resources()
```

```
1   cpu_resources()
```

```
1   gpu_resources()
```

```
1   accuracy_log(true_values, predictions, normalize=False)
```
true_values

predictions

normalize=False (Optional) the accuracy can be normalized but the default value is *False*

```
1   attackers_knowledge(attack)
```
attack This argument takes the executed attack function to poison the training data

```
1   attackers_goal()
```

```
1   positive_negative_label()
```

```
1   attack_time()
```

```
1   attack_specificty()
```

```
1   training_data()
```
x This argument takes the used training data

B. Case Study functions

class_num This argument gets the key value from the labels which is an integer.

train_number This argument gets the number of images from a labeled folder.

train_path This argument gets the path where the local training data is stored.

data_dir This argument gets the path where all local images are stored.

image_data This argument gets an array with all images from a label.

image_labels This argument gets the label which belongs to the corresponding images.

X_train This argument gets the training data.

attack Name of a backdoor attack as a string.

```
1    dataset_visualization(class_num, train_number)
```

With this function, the number of images are visualized and sorted from the lowest to the highest number of images per label.

```
1    read_training_data(train_path, data_dir)
```

This function reads in the training data, calls the *dataset_visualization()* function and resize the images to $30x30$ pixels. The function is called by the *preprocessing()* function.

```
1    preprocessing(train_path, data_dir, image_data, image_labels)
```

After calling the *read_training_data()* function, this function assign the **image_date** and **image_labels** arguments to shuffle the training data. Then the training data splits into training and validation data. The shape of the images must be reshaped for the SVM.

```
1    model_training(train_path, data_dir, image_data, image_labels)
```

After calling the *preprocessing()* function, this function calls the *KerasClassifier()* class which is an ART class to use Keras. This class must be used because the attacks only takes these classes for the proxy model training.

```
1    read_test_data(train_path, data_dir, image_data, image_labels)
```

After calling the *model_training()* function, this function reads in the test data, resizes the images to $30x30$ pixels and then reshape the images. The last step is the prediction with the test data.

```
1    create_model(X_train)
```

This function builds the ML model architecture for the classifier class of the ART.

```
1    model_finetuning()
```

This function is espacially for the *Hidden Trigger Backdoor Attack* because this attack must be executed while ML model finetuning.

```
1    create_attack(attack)
```

To call an attack this function must be called with an attack name.

C. Risk results template

At first, the evaluated measurement shows the risk matrix.

As next, the logged values are presented to show the raw data.

After that, the ML metrics are visualized.

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Selbständigkeitserklärung

Ich erkläre hiermit, dass ich die vorliegende Arbeit selbständig verfasst und noch nicht für andere Prüfungen eingereicht habe. Sämtliche Quellen einschließlich Internetquellen, die unverändert oder abgewandelt wiedergegeben werden, insbesondere Quellen für Texte, Grafiken, Tabellen und Bilder, sind als solche kenntlich gemacht. Mir ist bekannt, dass bei Verstößen gegen diese Grundsätze ein Verfahren wegen Täuschungsversuchs bzw. Täuschung eingeleitet wird.

Berlin, den 29. Mai 2022 ....