# Intrusion Detection System using KDD Cup 99 Dataset

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## ABSTRACT

Intrusion Detection System is a vital feature of protecting network infrastructure from unauthorized users or hackers. Intrusion detection system is used to identify several types of malicious activities that could effect the safety of network and to reduce network traffic. Because of faster growth of Internet, networks are growing rapidly in every area of society. As a result, large amount of data is travelling across many networks which may lead to vulnerability of integrity and confidentiality of data. Many Machine learning models are opened up providing new opportunity to classify traffic in network. In quest to select a good learning model, this paper illustrates performance between J48, Naive Bayes and Random forest classification models. The KDD Cup 99 dataset is used for experimental analysis to identify which classification model improves correctness of data and attains highest accuracy.

**Indexed terms**: Intrusion Detection, Machine Learning, KDD dataset, Classification models, Naive-bayes, J48, Random Forest, WEKA.

## INTRODUCTION

Network security is one of the major challenge facing in area of Computer Science. Security attacks are possible because of loopholes in designing of software and hardware. Intrusion Detection System(IDS) aid us to defend against vulnerable attacks. IDS acts as a shield to protect networks from malicious attacks and hackers[1]. IDS’s can be classified into two ways, either according to source of the events that they monitor like host events or network events, or according to the method they use to perform detection[2]. In general, there are two detection methods exists, namely signature based detection and anomaly based detection. In signature based detection, all defined patterns are compared with network pattern and the IDS is trained to recognize them. If any defined pattern matches with network pattern then the system is said to be attacked.However, signature based detection fails to detect new attacks since it will not have defined patterns for new attacks. In anomaly based detection,the normal behaviour of network traffic is defined and any network traffic which deviates from normal behaviour mean the network is under attack. Anomaly based detection can detect new attacks.Both techniques of IDS also have certain disadvantages. Neither of the techniques have proven to be much better than the other technique.Signature based detection reduces false alarm rate but it is unable to detect new attacks. Anomaly based detection can detect new attacks but may generate false alarm rates. Intrusion detection could be better if the input data was not manual and to be generated by a system itself by constantly learning like human.In this case, Machine learning classification models can be used which improves the system over time by learning from new data. Machine learning can be defined as “A computer program is set to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at task in T, as measured by P, improves with experience E.” Machine learning techniques can be categorized into supervised or unsupervised learning.

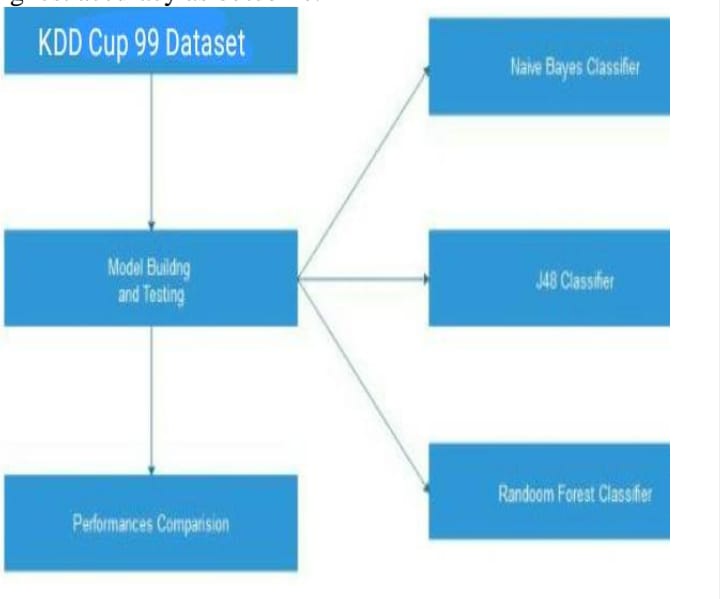
## LITERATURESURVEY

Thecomputernetworksystemsandtheirtechnologyrequireprevention from the threats, enemies and scandalous activities. In order topromise the integrity of computer network systems, security techniques arebeing brought in to a greater extent like antivirus software, firewalls andintrusion detection systems, etc.Intrusion detection system is a distinctiveprotection method which can find out unauthorized intrusion in a computernetwork or server. The IDS approaches are usually categorized into misuseand anomaly detection approaches in the literature. Misuse detection approachcanunfailinglyclassifyintrusionattacksinrelationtothewell-knownsignatures of discovered vulnerabilities. However, developing of a defenseexpert is required to characterize perfect rules or signatures that enhance thepurpose ofmisuse detectionapproach. Conversely, the anomaly detectiontechnique generally accords with statistical analysis and pattern recognitionproblems. It is capable of identifying new attacks without a priori knowledgeabout attacks. Many methods and frameworks have been developed to detectintrusions. Various techniques are also employed such as association rules,clustering,naiveBayesclassifier,supportvectormachines,geneticalgorithms, artificial neural networks, fuzzy logic and boosting algorithm, andothers have been applied to detect intrusions.

1. **PROBLEMSTATEMENT**

In this project, we will build a network intrusion detector, a predictive model capable of distinguishing between ‘’bad’’ connections, called as intrusions or attacks, and ‘’good’’ or normal connections. This dataset includes a wide variety of intrusions simulated in a military network environment. The data used to build the Intrusion detector was prepared and managed by MIT Lincoln Labs. The objective was to survey and evaluate research in intrusion detection.

## SYSTEM DESIGN

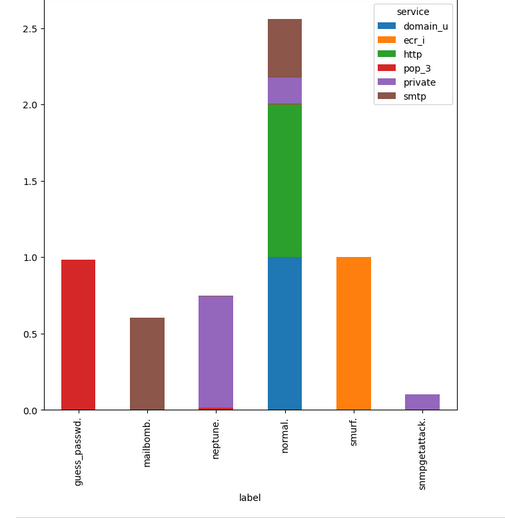


**Figure.1:**SystemDesign

A well-recognized KDD Cup 99 dataset was used to check performance analysis of various supervised classification techniques in testing phase. The KDD Cup 99 dataset is trained and tested by using Naive Bayes, J48, Random forest classification models. A machine learning open source tool named WEKA (Waikato Environment for Knowledge Analysis) was used for implementation. The above classification model attains highest accuracy as outcome. The methodology depicted in Figure 1 describes our machine learning model construction and implementation.

## IMPLEMENTATION

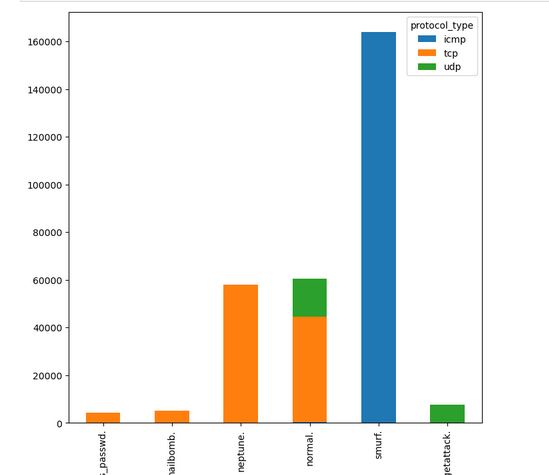
* 1. **DataCollection:**Gatheradiversedatasetoflungcancerimages,ensuringrepresentationacrossdifferentstagesandconditions.Acquirehigh-qualityimagesfromreliablemedicalsourcestoenhancethemodels'trainingefficacy.
  2. **Data Preprocessing:** Prepare the dataset by performing essential preprocessing steps, including resizing, normalization,andaugmentation,toensureuniformityandenhancethemodels'abilitytogeneralize.
  3. **ModelSelectionandImplementation:**ChooseEfficientNetB3,ResNet50,andInceptionV3asthedeeplearningmodelsforlungcancerimageanalysis.ImplementthesemodelsusingpopularframeworkssuchasTensorFloworPyTorch.



* 1. **ModelTraining:**Traintheselecteddeeplearningmodelsonthepreprocesseddataset.Fine-tunethemodels'hyperparameterstooptimizeperformance,employingtechniquessuchastransferlearningtoleveragepre-trainedweights.
  2. **PerformanceEvaluation:**Evaluatethetrained models using key metrics such as accuracy, precision, recall, andF1-score. Conduct comprehensive testing on a separate validation dataset to assess the models' ability to generalize to new,unseencases.

## Testing

* 1. **Create a Subset of Main Database**

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1. **Result**

| **Name** | **description** | **Type** |
| --- | --- | --- |
| duration | number of seconds of connection | continuous |
| protocol\_type | type of protocol used *(eg:tcp, udp, etc)* | discreet |
| service | network service type at destination *(eg http, telnet)* | discreet |
| src\_bytes | number of bytes transferred from source to destination | continuous |
| dst\_byte | data numbers transferred from destination to origin | continuous |
| Flag | connection error status | discreet |
| Land | 1 if the connection is to the same host / port | discreet |
| wrong\_fragments | wrong number of fragments | continuous |
| urgent | number of urgent packages | continueous |

This shows that duplicate data actually *skews* the classifier to the records most often, and thus decreases the accuracy of the model.

## CONCLUSION AND FUTURE SCOPE

In conclusion, this proposed work aims to contribute significantly to the field of intrusion detection by developing a robust mathematical model that leverages stateful protocol analysis on the KDD Cup 99 dataset. By addressing the specific objectives outlined, including the identification of stateful protocol feature patterns, feature extraction and selection, and model development using supervised machine learning techniques, the study seeks to advance the state-of-the-art in safeguarding computer networks against evolving security threats.

The identification and analysis of stateful protocol feature patterns represent a departure from traditional intrusion detection approaches, which often focus on individual network features. By recognizing the complex sequences of network events inherent in modern attacks, the study aims to enhance the ability of intrusion detection systems to detect and mitigate potential threats to network integrity and confidentiality.

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