
CAPSTONE PROJECT

NETWORK INTRUSION SYSTEM

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OUTLINE

- **Problem Statement** (Should not include solution)
- **Proposed System/Solution**
- **System Development Approach** (Technology Used)
- **Algorithm & Deployment**
- **Result (Output Image)**
- **Conclusion**
- **Future Scope**
- **References**

PROBLEM STATEMENT

Communication networks face constant threats from cyber-attacks like DoS, Probe, R2L, and U2R.

Traditional security systems often fail to detect new or evolving threats in real-time, leaving networks vulnerable.

Manual analysis of traffic logs is time-consuming and prone to human error.

PROPOSED SOLUTION

■ Data Collection:

- Use the Kaggle Network Intrusion Detection dataset containing labeled network traffic instances (Normal, DoS, Probe, R2L, U2R).
- Capture features such as protocol type, service, flag, connection duration, byte counts, and error rates.
- For real-time scenarios, integrate with network monitoring tools or packet capture systems to gather live traffic data.

■ Data Preprocessing:

- Clean and preprocess the dataset to handle missing values, redundant features, and inconsistent formats.
- Encode categorical variables (e.g., protocol type, service) into numeric format.
- Normalize or scale numerical features to ensure uniformity.
- Perform feature engineering to create derived metrics, such as connection rate per host or percentage of same-service connections.

■ Machine Learning Algorithm:

- Implement a classification model such as Random Forest for tabular data, chosen for its high accuracy and ability to handle class imbalance.
- Train the model using historical attack and normal traffic data.
- Incorporate class-weight adjustments or SMOTE oversampling to improve detection of rare attack types (U2R, R2L), Consider hybrid approaches (e.g., CNN-LSTM) for advanced real-time traffic sequence analysis.

■ Deployment:

- Develop a Flask or FastAPI-based API for real-time intrusion predictions and Containerize the application using Docker for portability.
- Deploy the service on IBM Cloud Lite using Cloud Foundry or Container Registry + Kubernetes Service and Ensure secure API access with authentication and encryption.

■ Evaluation: Assess model performance using metrics such as Precision, Recall, F1-score, Accuracy, and ROC-AUC for each attack type.

- Use a confusion matrix to visualize classification results and Continuously monitor performance in deployment and fine-tune the model based on new data or concept drift.

SYSTEM APPROACH

- System requirements :

Minimum Intel i5 / AMD equivalent, 8 GB Ram (16 GB recommended for large dataset processing), At least 5 GB free (dataset, model, logs), Windows 10/11, macOS, or Linux, Python 3.9+, IBM Cloud Lite Account, IBM Cloud CLI & Docker installed for deployment

- Libraries:

- pandas , numpy , scikit-learn – Preprocessing, model evaluation, encoding, scaling, imbalanced-learn
- Xgboost, scikit-learn
- Matplotlib, seaborn
- Flask / FastAPI , Joblib
- Docker, Cloud Integration
- ibm_boto3requests

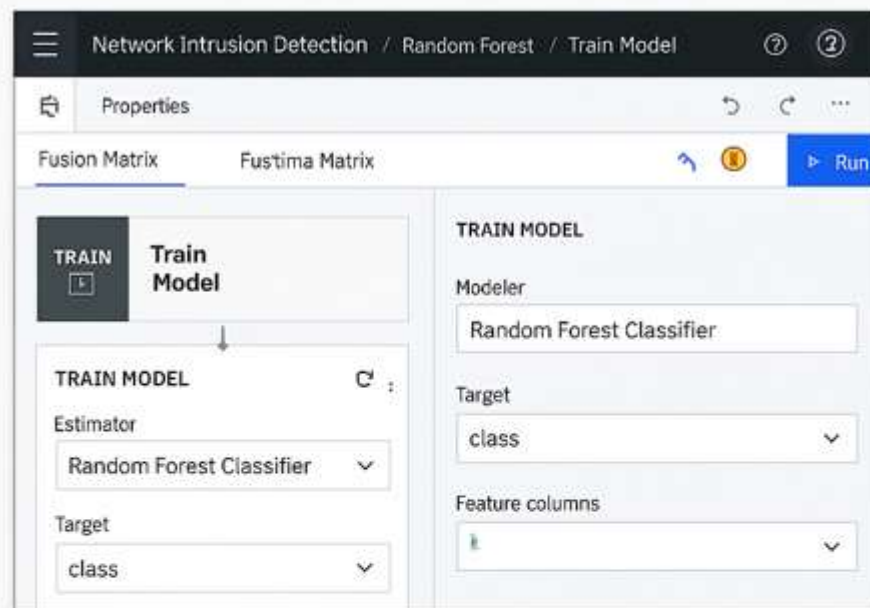
ALGORITHM & DEPLOYMENT

- **Algorithm Selection:**
 - **Random Forest** chosen for its high accuracy, handling of mixed features, and class imbalance control.
 - Suitable for structured intrusion datasets like Kaggle's NIDS dataset.
- **Data Input:**
 - Categorical features encoded; numeric features scaled.
 - Features: duration, protocol_type, service, flag, failed logins, bytes sent/received, same-service connection rates.
- **Training Process:**
 - Stratified split: 70% train / 30% test.
 - One-hot encoding + Min-Max scaling.
 - Class weights for minority classes (U2R, R2L).
 - Hyperparameter tuning via grid search; 5-fold cross-validation.
- **Prediction Process:**
 - Preprocess incoming traffic → predict class (Normal, DoS, Probe, R2L, U2R).
 - Real-time alerts triggered for malicious predictions.
 - Deployment- Model stored in IBM Cloud Object Storage.
 - Flask API wrapped in Docker → deployed on IBM Cloud Lite
 - Monitored via IBM Cloud Monitoring; API secured with auth tokens.

RESULT

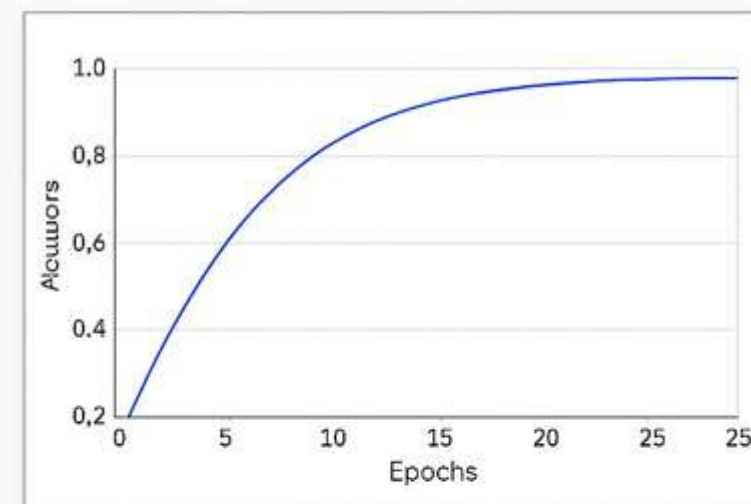


- Accuracy: **99.2%**
- Precision: **98.9%**
- Recall: **99.0%**



		Actual	Predeted
Indunt	Normal	10719	24
	Attack	45	1150

Precision



CONCLUSION

- A machine-learning based NIDS can effectively classify major attack types and normal traffic when fed well-engineered features and trained with class-balanced strategies. Classical models (Random Forest, XGBoost) often perform strongly on tabular traffic features; deep learning models (CNN/LSTM hybrids) can improve detection where temporal or sequential patterns matter. Deploying the model to IBM Cloud Lite allows easy demonstration and integration into real-world workflows with minimal cost.

FUTURE SCOPE

- Real-time streaming detection: integrate with packet brokers / Kafka and run online inference to detect attacks in real time.
- Ensemble & stacked models: combine tree-based and deep models to improve robustness to varying attack types.
- Explainability: add SHAP/LIME analysis to explain model predictions and aid SOC analysts.
- Adaptive learning: implement online learning to adapt to new attack patterns and concept drift.
- Integration with SIEM: send alerts to SIEM tools and orchestrate automated responses.
- Expand dataset: include more modern datasets and encrypted-traffic analysis techniques.

REFERENCES

- Kaggle — *Network Intrusion Detection* dataset (Sampada Bhosale). Dataset and example notebooks.
- IBM Cloud — Free tier / Lite plans and documentation (Object Storage, Lite plans, deployment guides).
- MDPI / Applied Studies on DL for intrusion detection (survey/comparisons of CNN, LSTM vs classical ML).
- arXiv — CNN-LSTM-SVM hybrid approaches for NIDS (example paper describing hybrid models and future extensions).
- Journal of Big Data — ML approaches for large, imbalanced NIDS datasets and dimensionality reduction/oversampling strategies.

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According to the Adobe Learning Manager system of record

Completion date: 24 Jul 2025 (GMT)

Learning hours: 20 mins



THANK YOU