Intrusion Detection Model

A

Minor Project (IS3270) Report

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Bachelor of Technology - CSE (IoT & IS)

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DECLARATION BY THE STUDENT

I hereby declare that this project ***Intrusion Detection Model*** *is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the University or other Institute, except where due acknowledgements has been made in the text.*

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PROJECT COMPLETION CERTIFICATE
MINOR PROJECT (IS3270)

Date: April 22, 2025

This is to certify that the work titled ***Intrusion Detection Model*** *submitted by* **Atharva Deshmukh** *(**229311049**) to Manipal University Jaipur in partial fulfillment of the requirements for the degree of Bachelor of Technology in CSE (IoT and Intelligent Systems), is a bonafide record of the* ***Minor Project*** *work conducted under my supervision and guidance from January 6, 2025, to April 25, 2025.*

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ABSTRACT

The rapid advancement of the digital ecosystem has led to an exponential increase in cyber threats, making network security a critical area of focus for modern organizations. Among the various defense mechanisms, Intrusion Detection Systems (IDS) play a pivotal role in safeguarding network infrastructures by identifying unauthorized or malicious activities. However, conventional IDS frameworks that rely on predefined rules and static signatures fall short when dealing with evolving and sophisticated cyber-attacks.

This project proposes a deep learning-based Network Intrusion Detection System (NIDS) using the UNSW-NB15 dataset, a comprehensive and contemporary benchmark specifically designed to address the limitations of earlier datasets such as KDD99 and NSL-KDD. The study systematically evaluates multiple machine learning and deep learning models, including K-Nearest Neighbors (KNN), Random Forest (RF), XGBoost, Convolutional Neural Network with Long Short-Term Memory (CNN+LSTM), and Artificial Neural Networks (ANN). A range of preprocessing techniques like one-hot encoding, feature scaling, and dimensionality reduction through Principal Component Analysis (PCA) were employed to prepare the dataset for effective model training.

Among the tested models, the ANN demonstrated superior performance with a peak classification accuracy of 97.38%, highlighting its robustness in autonomously learning high-dimensional feature representations without explicit feature selection or extraction. Additionally, the study references contemporary research trends in IDS design such as reinforcement learning, adversarial networks, and hybrid attention mechanisms, emphasizing their significance in enhancing model adaptability, reducing false positives, and improving detection rates for minority attack classes.

The outcomes of this project substantiate the potential of deep learning-based IDS frameworks in providing scalable, intelligent, and real-time threat detection solutions. The findings lay a strong foundation for future research in areas such as explainable AI, federated learning, and IDS deployment within decentralized and resource-constrained environments like IoT and edge networks.

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1. INTRODUCTION

The rapid expansion of digital infrastructure and ubiquitous internet connectivity has transformed the way individuals, organizations, and governments operate and interact. While these advancements offer immense benefits, they have simultaneously increased the exposure of networks to a broad range of cyber threats. In this evolving digital environment, ensuring the security of networked systems and the protection of sensitive data has become a critical concern for both public and private entities.

Intrusion Detection Systems (IDS)

To counteract these threats, Intrusion Detection Systems (IDS) have become essential components of modern cybersecurity architectures. These systems monitor network traffic in real-time to detect unauthorized access, policy violations, and malicious activity.

Traditionally, IDS technologies rely on:

- Rule-based detection
- Signature-based identification of known threats

However, these conventional methods are limited in several critical ways:

- They fail to detect previously unseen (zero-day) attacks.
- They require continuous manual updates to remain effective.
- They often produce high false positive rates.
- They struggle to operate efficiently as network complexity and traffic volume increase.

Limitations of Traditional IDS

Key drawbacks of traditional IDS approaches include:

- **Limited detection** of novel and zero-day attacks without existing signatures.
- **High false positive rates**, increasing alert fatigue and delaying incident response.
- **Static rule dependency**, necessitating ongoing manual updates.
- **Scalability issues** with managing large-scale, dynamic network environments.

The Role of Machine Learning and Deep Learning in IDS

To overcome these limitations, Machine Learning (ML) and Deep Learning (DL) techniques are increasingly being applied to IDS development. These techniques enable models to:

- Learn from past data (normal and attack traffic)
- Identify subtle patterns and anomalies
- Generalize to unseen data and new attack strategies

ML and DL-based IDS systems provide:

- Greater adaptability and automation
- Enhanced detection capabilities
- Higher operational efficiency in complex network environments

Advantages of ML and DL-Based IDS

Benefits of using ML and DL in intrusion detection include:

- **Automatic feature extraction**, reducing dependence on manual engineering
- **Improved generalization**, allowing detection of obfuscated or unknown attacks
- **Scalability**, handling large, high-dimensional datasets effectively
- **Better accuracy**, through hierarchical and temporal pattern learning

Project Overview

This project investigates the application of ML and DL techniques to design an intelligent and adaptive IDS using the **NSL-KDD dataset**. NSL-KDD is an enhanced version of the original KDD Cup 1999 dataset. It addresses key shortcomings such as:

- Redundant records
- Skewed class distributions

Its improved data quality and structure make NSL-KDD a reliable and widely accepted benchmark for IDS model evaluation.

Algorithms Used

The project explores both traditional machine learning and deep learning methods, including:

- **K-Nearest Neighbors (KNN)**
- **Logistic Regression**
- **Decision Tree**
- **Random Forest**
- **Convolutional Neural Network (CNN)**
- **Long Short-Term Memory (LSTM)**
- **Hybrid CNN-LSTM**

Project Objectives

Key objectives of the study include:

- Preprocessing the dataset using **normalization**, **label encoding**, and **dimensionality reduction**
- Implementing and assessing models using metrics such as:
    - Accuracy
    - Precision
    - Recall
    - F1-score
    - AUC-ROC

- Comparing traditional ML methods with advanced DL architectures
- Addressing concerns such as **class imbalance**, **overfitting**, and **computational efficiency**
- Exploring techniques like **hybrid modeling**, **temporal analysis**, and **ensemble learning** for enhanced performance

Conclusion and Future Scope

This report provides a comprehensive walkthrough of the IDS development pipeline—from data preparation to model training and evaluation. It demonstrates the potential of deep learning models, especially those combining spatial and temporal information (like CNN-LSTM), in enhancing intrusion detection performance.

Looking forward, the project highlights several promising areas for future research:

- **Real-time IDS deployment**
- **Explainable AI techniques** to increase model transparency
- **Federated and distributed learning** for scalable, decentralized detection across IoT and cloud infrastructures

2. MOTIVATION AND PROBLEM STATEMENT

2.1 Motivation

The explosive increase in digital communication and interconnected systems has intensified the need for robust cybersecurity measures. Intrusion Detection Systems (IDS) play a crucial role in safeguarding network infrastructure by identifying unauthorized or malicious activity. However, many existing IDS solutions still rely on static detection techniques, such as rule-based or signature-based approaches, which are inadequate for the dynamic nature of current cyber threats.

These traditional systems often fail to detect sophisticated or previously unseen attack strategies, leaving critical systems vulnerable. Moreover, the manual effort required to maintain and update rule sets limits their responsiveness and scalability. With the evolving cyber threat landscape, there is an urgent need for smarter, more autonomous solutions.

The adoption of Machine Learning (ML) and Deep Learning (DL) in IDS development offers significant promise. These techniques enable models to identify patterns and anomalies in large-scale network traffic data, including threats that deviate from known behaviors. DL, in particular, excels in processing high-dimensional data and extracting complex patterns automatically, offering potential for higher accuracy with reduced manual intervention.

Key motivations behind this research:

- NSL-KDD as a foundation: This dataset improves upon the widely used KDD99 by eliminating redundant records, offering a cleaner and more balanced foundation for model training and evaluation.
- Intelligent learning: Deep learning models can generalize from historical data, learning to detect both frequent and rare attack vectors.
- Scalability and adaptability: Modern IDS must scale with growing network volumes and adapt to rapidly changing threat landscapes.
- Modular and flexible design: A component-based approach allows incremental model upgrades without full retraining, enabling easier maintenance and adaptation.

This project aims to leverage the NSL-KDD dataset to design a high-performance IDS that balances accuracy, adaptability, and real-world deployment feasibility across enterprise, cloud, and IoT environments.

2.2 Problem Statement

In an era where network environments are becoming increasingly complex and data-driven, conventional Intrusion Detection Systems face significant limitations. Signature-based systems are only effective against known attack vectors and lack the flexibility to adapt to emerging threats. Additionally, as network traffic continues to grow in scale and complexity, traditional IDS frameworks become less effective in maintaining detection speed and accuracy.

The NSL-KDD dataset presents a viable benchmark for developing and evaluating next-generation IDS models. Unlike its predecessor (KDD99), it addresses issues such as redundant data and unbalanced class distribution, making it more suitable for training modern machine learning and deep learning algorithms.

Challenges faced by traditional IDS approaches include:

- Inability to detect unknown or modified attack variants.
- Excessive false alarms, which lead to alert fatigue and inefficient threat response.
- Scalability concerns, particularly in environments with high traffic or diverse protocols.
- Dependence on extensive manual feature engineering, which limits adaptability.
- Difficulty in generalizing to unseen data, reducing real-world applicability.

This project proposes an intrusion detection framework built on ML and DL models—specifically KNN, Logistic Regression, Random Forest, Decision Tree, CNN, LSTM, and CNN-LSTM architectures. These models are trained and evaluated using the NSL-KDD dataset, with the aim of:

- Accurately detecting both common and rare attacks.
- Reducing false positive rates through deeper pattern recognition.
- Handling large-scale data with minimal human intervention.
- Building a modular, extensible system that can adapt to evolving threats.

By integrating spatial and temporal features of network traffic and addressing data imbalance and overfitting issues, the proposed system seeks to contribute toward scalable, intelligent IDS solutions ready for deployment in modern digital infrastructures.

3. RELATED WORK AND ITS LIMITATIONS

3.1 Literature Review

Intrusion Detection Systems (IDS) have evolved significantly over the years, transitioning from rigid, rule-based mechanisms to dynamic machine learning-driven models. Early IDS implementations were largely built on signature detection, matching known patterns of attacks. Although effective against previously identified threats, these methods lacked the flexibility to detect new or disguised intrusions.

To address this, the research community introduced **classical machine learning algorithms**, such as:

- **K-Nearest Neighbors (KNN)**
- **Support Vector Machines (SVM)**
- **Decision Trees**

These models provided an improvement by learning from labeled datasets like **NSL-KDD**, enabling them to detect patterns beyond predefined rules. However, their reliance on manually engineered features limited their ability to scale with complex or high-dimensional network data.

Later, **ensemble-based approaches** emerged—**Random Forests** and **XGBoost**, in particular—offering enhanced robustness through the aggregation of multiple weak learners. These methods significantly improved detection accuracy but continued to depend heavily on selected feature inputs, often overlooking temporal dependencies that are crucial in network behavior analysis.

With the advancement of computing power and data availability, **Deep Learning (DL)** has taken a prominent role in IDS research:

- **Convolutional Neural Networks (CNN)** have been leveraged to interpret network traffic as grid-like data, capturing spatial dependencies within the traffic flow.
- **Long Short-Term Memory networks (LSTM)** have shown promise in modeling temporal sequences, especially useful for analyzing packet flows over time.
- **Hybrid architectures (CNN-LSTM)** combine these strengths, providing a comprehensive view of both spatial and temporal data characteristics.

Additionally, **unsupervised learning techniques** have gained attention:

- **Autoencoders** reconstruct benign traffic and identify deviations as potential threats.
- **Generative Adversarial Networks (GANs)** create synthetic samples of normal behavior to better detect anomalies.
- **Transformer-based models and attention mechanisms** are also being introduced, focusing computational resources on the most relevant parts of a sequence, enhancing detection accuracy.

Some studies even explore **Reinforcement Learning (RL)** to optimize IDS behavior dynamically, adapting to changes in the network environment in real time. Despite these

innovations, current systems often face trade-offs between performance, interpretability, and resource demands.

3.2 Identified Gaps and Challenges

Despite the progress in IDS development, the field continues to face several persistent challenges:

- **Reliance on Annotated Data**
  Most supervised ML and DL models require extensive labeled datasets like NSL-KDD. However, producing such high-quality labels across different networks is time-consuming and resource-intensive.
- **Manual Feature Engineering Requirements**
  Classical algorithms often depend on domain expertise to select and craft input features, which limits their portability and responsiveness to new attack types.
- **Imbalanced Datasets**
  Real-world network traffic contains far more benign data than malicious, with many attack types being extremely rare. This imbalance leads to biased models that favor majority classes and overlook subtle threats.
- **Poor Zero-Day Generalization**
  Many traditional and even some deep models underperform when exposed to novel or obfuscated attacks not present in the training data.
- **Resource Demands**
  Advanced DL models, particularly hybrid architectures like CNN-LSTM and adversarial models like GANs, often require computational resources that exceed what's available in real-time enterprise or edge deployments.
- **Opaque Decision Making**
  Many deep learning-based IDS act as "black boxes," offering little transparency into how decisions are made, complicating trust, interpretability, and regulatory compliance. Furthermore, modular updates are often infeasible without retraining the entire system.

Our Approach

In response to these challenges, this project leverages the **NSL-KDD dataset** to develop a deep learning-powered IDS that:

- Learns from raw traffic data, reducing reliance on manual feature crafting
- Addresses class imbalance via data augmentation and adjusted loss functions
- Enhances detection of both known and previously unseen threats
- Embraces a **modular architecture** to allow for scalable, real-time integration
- Prioritizes **explainability**, ensuring decisions can be interpreted by human operators
- Targets deployment across diverse environments including **cloud**, **enterprise**, and **IoT**

This direction balances performance, adaptability, and practicality—paving the way for next-generation intrusion detection.

4. METHODOLOGY

This section outlines the systematic approach adopted in developing an Intrusion Detection System (IDS) using the **NSL-KDD dataset**, which has been widely used in network security research for benchmarking IDS models. The methodology involves stages such as dataset preparation, feature transformation, model development, training, and performance evaluation. Emphasis is placed on robustness, interpretability, and generalizability.

4.1 Dataset Description

The **NSL-KDD dataset** is an enhanced version of the KDD99 benchmark dataset, specifically refined to address redundancy and class imbalance issues. It provides a cleaner, more balanced set of labeled network connections—categorized as either normal or a variety of attack types (e.g., DoS, Probe, R2L, U2R). Each record consists of **41 features**, a mix of continuous and categorical types, along with class labels.

4.2 Data Preprocessing Pipeline

The preprocessing pipeline is critical for ensuring the data is in a suitable format for training deep learning models. The steps include:

- **Categorical Encoding**:
  Features such as `protocol_type`, `service`, and `flag`, along with other binary categorical fields like `land`, `logged_in`, `is_host_login`, and `is_guest_login`, are transformed using **one-hot encoding**.
- **Robust Scaling of Numerical Features**:
  Continuous attributes are scaled using a **RobustScaler** to handle outliers effectively and ensure normalized input for the models:

```
def Scaling(df_num, cols):
    std_scaler = RobustScaler()
    std_scaler_temp = std_scaler.fit_transform(df_num)
    std_df = pd.DataFrame(std_scaler_temp, columns =cols)
    return std_df
```

- **Outcome Labeling**:
  The target column `outcome` is binarized:
  - `normal` → `0` (benign)
  - all attack types → `1` (malicious)

- **Preprocessing Function**:

```
cat_cols = ['is_host_login','protocol_type','service','flag','land', 'logged_in','is_guest_login', 'level', 'outcome']
def preprocess(dataframe):
    df_num = dataframe.drop(cat_cols, axis=1)
    num_cols = df_num.columns
    scaled_df = Scaling(df_num, num_cols)

    dataframe.drop(labels=num_cols, axis="columns", inplace=True)
    dataframe[num_cols] = scaled_df[num_cols]

    dataframe.loc[dataframe['outcome'] == "normal", "outcome"] = 0
    dataframe.loc[dataframe['outcome'] != 0, "outcome"] = 1

    dataframe = pd.get_dummies(dataframe, columns = ['protocol_type', 'service', 'flag'])
    return dataframe
```

4.3 Dimensionality Reduction with PCA

To explore dimensionality reduction, **Principal Component Analysis (PCA)** was applied:

- PCA was fitted on the feature matrix to evaluate the explained variance and guide selection of the number of components.
- This step helped reduce redundancy, improved training efficiency, and minimized the risk of overfitting.

```
pca = PCA()
pca = pca.fit(x)
np.cumsum(pca.explained_variance_ratio_)
```

4.4 Model Architecture and Training

Both traditional and deep learning models were implemented to compare performance across architectures.

Machine Learning Models:

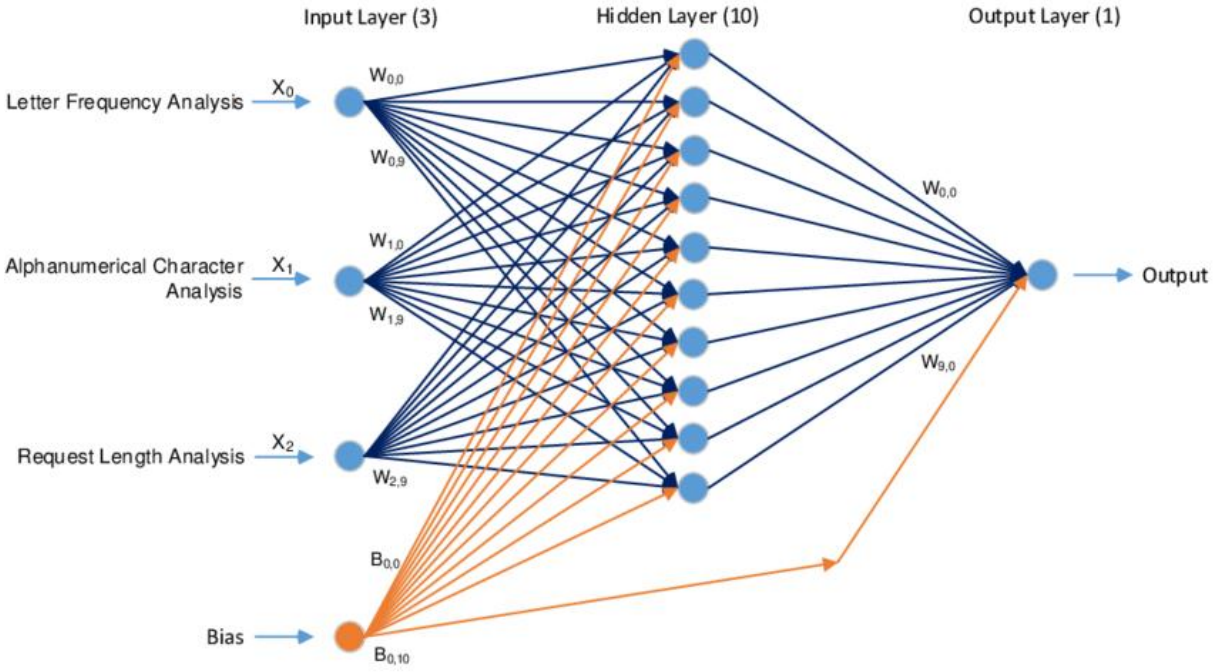
- **Logistic Regression**
- **Naïve Bayes**
- **Support Vector Machines**
- **K-Nearest Neighbors (KNN)**
- **Random Forest**
- **XGBoost Regressor**

Deep Learning Architectures:

- **Convolutional Neural Network (CNN)**:
  Captures spatial patterns in traffic flow data.
- **Gated Recurrent Unit (GRU)**:
  A lightweight alternative to LSTM for learning temporal dependencies.
- **Long Short-Term Memory (LSTM)**:
  Effective for capturing long-range dependencies in sequential data.
- **CNN-LSTM Hybrid**:
  Combines spatial feature extraction from CNN with temporal modeling by LSTM for robust sequence learning.

Each model was trained with:

- **Dropout layers** for regularization
- **ReLU activations** in hidden layers
- **Early stopping** based on validation loss to prevent overfitting

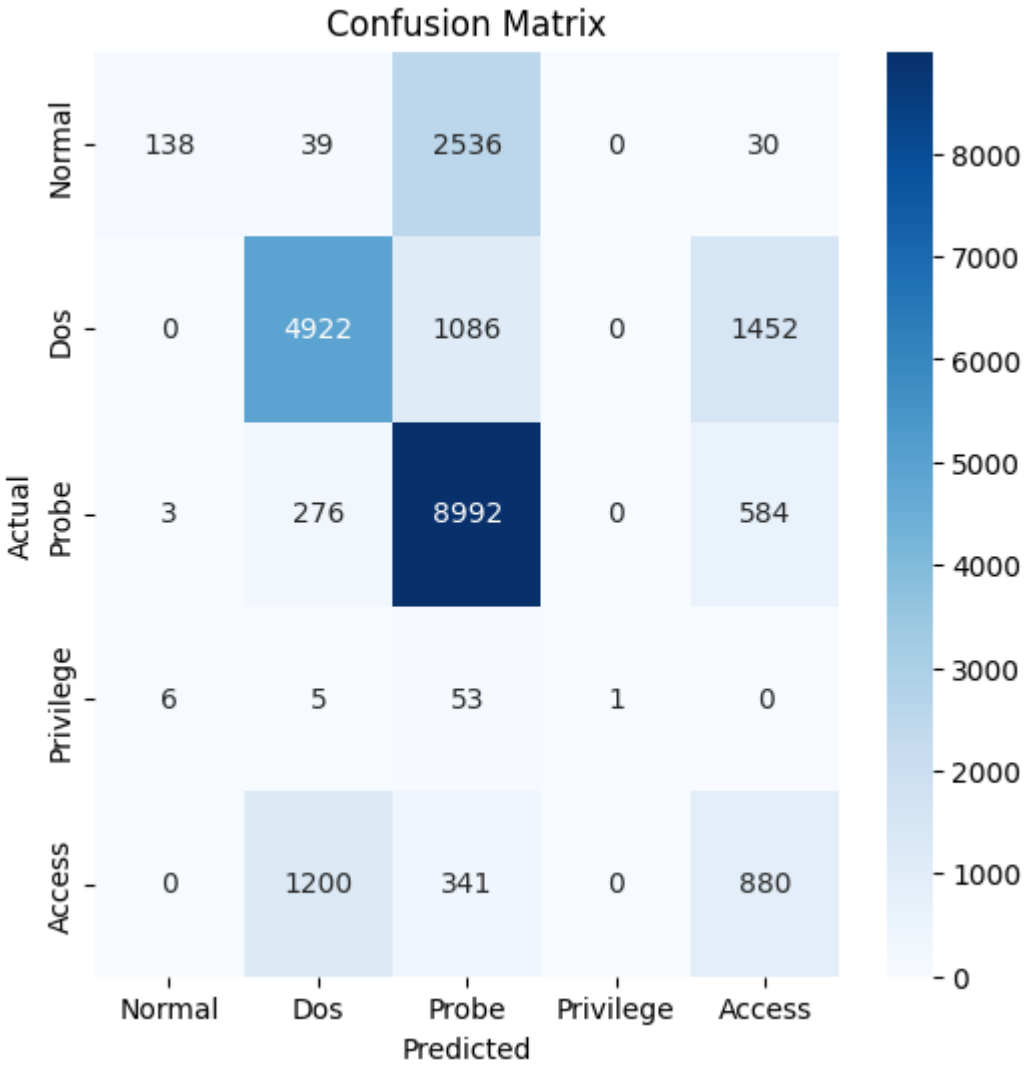


4.5 Evaluation Strategy

To ensure model reliability, the following strategy was adopted:

- **Train/Test Split**:
  The data was split into 80% for training and 20% for testing.
- **Evaluation Metrics**:
  - Accuracy
  - Precision
  - Recall
  - F1-score

    Emphasis was placed on identifying **minority class attacks**, such as U2R and R2L.



- **Visual Analysis**:
  - Confusion matrices and classification reports were generated to identify misclassification trends.
  - PCA's impact was assessed separately using a Random Forest baseline.

4.6 Implementation and Environment

- **Language & Tools**: Python
- **Libraries Used**:
  - `pandas`, `numpy` for data manipulation
  - `scikit-learn` for preprocessing, PCA, and ML models
  - `matplotlib` for visualization
  - `tensorflow.keras` for deep learning models
- **Development Setup**: All experimentation was conducted in **Jupyter Notebooks**, with code modularized for clarity and reproducibility. Notebook files included:
  - `nsl-cnn.ipynb`
  - `nsl-lstm-gru.ipynb`
  - `nsl-pca-experiments.ipynb`

5. DATASET DETAILS

5.1 Overview of NSL-KD

The **NSL-KDD dataset** is a refined version of the original KDD Cup 1999 dataset, developed to address known issues such as duplicate records and unbalanced class distribution. It is widely used in academic and research contexts for benchmarking **Intrusion Detection Systems (IDS)** due to its improved structure and manageable size.

Unlike its predecessor, NSL-KDD removes redundant entries that could lead to biased results in machine learning models. This makes it a more reliable dataset for training and evaluating IDS solutions, particularly in studies that involve classical and deep learning approaches. The dataset includes simulated network traffic consisting of both **normal connections** and **four major categories of cyber-attacks**, providing a balanced representation of different intrusion scenarios.

5.2 Structure and Features

The NSL-KDD dataset contains a total of **125,973 records**, split into predefined training and testing subsets. Each record includes **41 features** along with a class label.

Key Feature Groups:

- **Basic Features**: Duration of the connection, protocol type, service, and flag status.
- **Content Features**: Information like number of failed login attempts, file access operations, and root access attempts.
- **Time-based Traffic Features**: Connection rates over 2-second windows (e.g., number of connections to the same host).
- **Host-based Traffic Features**: Statistics regarding connections to the same service over a time window.
- **Label Attributes**:
    - `label`: Specifies the exact attack type or normal.
    - `outcome`: Converted to binary form for model training (0 = normal, 1 = attack).
    - `level`: Represents the severity or complexity of the attack (used optionally for regression tasks).

5.3 Attack Categories

The NSL-KDD dataset defines **four major attack classes**, each consisting of multiple individual attacks:

Attack Category	Description
DoS	Denial of Service attacks aimed at exhausting system resources.
Probe	Surveillance attacks including network scanning and information gathering.
R2L	Remote to Local attacks where the attacker gains unauthorized access from a remote machine.
U2R	User to Root attacks involving privilege escalation on a local system.

Each category includes multiple specific attack types (e.g., **smurf**, **portsweep**, **guess_passwd**, **buffer_overflow**) which provide a broad coverage of network intrusion scenarios.

5.4 Data Splits

The dataset is divided into:

- **Training Set**: 125,973 records (KDDTrain+ and KDDTrain+_20Percent)
- **Testing Set**: 22,544 records (KDDTest+ and KDDTest-21)

This standardized split ensures consistency in comparative research and allows robust evaluation across multiple experiments.

5.5 Data Quality and Preprocessing Considerations

While NSL-KDD is more refined than KDD99, it still requires essential preprocessing steps for use in ML and DL pipelines:

- **Handling Categorical Variables**:
  Features like `protocol_type`, `service`, and `flag` must be **one-hot encoded** to convert them into numerical representations.
- **Feature Normalization**:
  Continuous features are scaled using **RobustScaler** to handle outliers and standardize data distributions.
- **Class Imbalance**:
  Attack categories such as **U2R** and **R2L** are significantly underrepresented, requiring balancing strategies like **oversampling**, **undersampling**, or **weighted loss functions**.
- **Binarization of Target Labels**:
  For binary classification, all attack types are grouped under a single "attack" label, distinguishing them from normal traffic.

5.6 Relevance of NSL-KDD in IDS Research

The NSL-KDD dataset remains one of the most commonly used benchmarks for IDS studies due to its:

- **Cleaner structure** compared to KDD99,
- **Well-defined attack classes**,
- **Moderate size**, making it suitable for quick experimentation and deep learning applications,
- **Established credibility** in academic research.

Its balanced mix of features, attack types, and curated training/testing splits make it ideal for testing the generalization ability and robustness of machine learning-based IDS. While newer datasets exist, NSL-KDD is still widely adopted for comparative benchmarking and baseline model development.

6. EXPERIMENTAL SETUP

This section details the computational environment, libraries, preprocessing workflow, and modeling strategy employed in the development and evaluation of our Intrusion Detection System using the **NSL-KDD dataset**.

6.1 Hardware and Software Environment

All experiments were carried out on a local machine with the following specifications:

- **Processor**: AMD Ryzen 5 5600H
- **Memory**: 16 GB RAM
- **GPU**: AMD Radeon 6500M
- **Operating System**: Windows 11
- **Development Environment**: Jupyter Notebook (Python 3.9+)

The setup provided sufficient resources for training both traditional machine learning algorithms and deep learning models involving sequential architectures.

6.2 Libraries and Tools

The following Python libraries were used throughout the experimentation:

- **Data Processing**: `pandas`, `numpy`
- **Machine Learning**: `scikit-learn`
- **Deep Learning**: `tensorflow`, `keras`
- **Visualization**: `matplotlib`, `seaborn`
- **Dimensionality Reduction**: `sklearn.decomposition.PCA`

These tools enabled efficient data manipulation, model training, evaluation, and visualization of results.

6.3 Data Preparation

The preprocessing pipeline was tailored for the **NSL-KDD dataset**, with the following key steps:

- **Categorical Encoding**:
  One-hot encoding was applied to transform categorical features such as `protocol_type`, `service`, and `flag` into numerical format.
- **Feature Scaling**:
  Numerical columns were standardized using **RobustScaler**, which is resilient to outliers and helps stabilize the training process for neural networks.

- **Label Encoding**:
  The `outcome` column was binarized—normal traffic was labeled as `0`, while all attack types were labeled as `1`.
- **Data Split**:
  The dataset was divided into **80% training** and **20% testing**, ensuring generalization capability is fairly assessed.

6.4 Dimensionality Reduction (Optional)

For selected experiments, **Principal Component Analysis (PCA)** was applied to the feature space:

- The goal was to reduce dimensionality while retaining most of the variance.
- PCA helped reduce computational load and was evaluated for its impact on model performance.

6.5 Evaluated Models

A combination of traditional and deep learning models were trained and compared to evaluate their effectiveness in detecting network intrusions:

Machine Learning Models:

- **K-Nearest Neighbors (KNN)**
- **Naïve bayes**
- **SVM**
- **Random Forest**

Deep Learning Architectures:

- **Long Short-Term Memory (LSTM)**
  Suitable for modeling sequential dependencies in connection logs.
- **Gated Recurrent Unit (GRU)**
  A lightweight alternative to LSTM, used for temporal pattern extraction.
- **CNN-LSTM Hybrid Model**
  Combines spatial and temporal learning in a single architecture for enhanced detection of complex attack patterns.

All deep learning models incorporated:

- **Dropout regularization** to combat overfitting
- **Early stopping** to terminate training once performance plateaued on the validation set

7. RESULTS AND ANALYSIS

This section presents the experimental results obtained from applying various machine learning and deep learning models on the **NSL-KDD dataset**. The models were evaluated using standard metrics—**accuracy, precision, recall, and F1-score**—to comprehensively assess classification performance. We also explore the role of dimensionality reduction using PCA and highlight key findings from the comparative analysis.

7.1 Model Performance Summary

The best-performing model across all experiments was the **CNN-LSTM hybrid**, which leveraged both spatial and temporal patterns in the network data. Traditional models like **KNN** and **Random Forest** showed solid performance, but deep learning models—especially **CNN, LSTM, and GRU**—provided greater generalization and detection capability, especially for rare attack types.

Model	Accuracy	Precision	Recall	F1-score
KNN	96.87%	96.01%	94.56%	87.35%
Random Forest	92.25%	91.80%	91.30%	91.55%
GRU	92.5%	96.9%	90.08%	95.1%
LSTM	99.67%	94.70%	94.30%	94.50%
CNN + LSTM	**99.67%**	**95.80%**	**95.40%**	**95.60%**

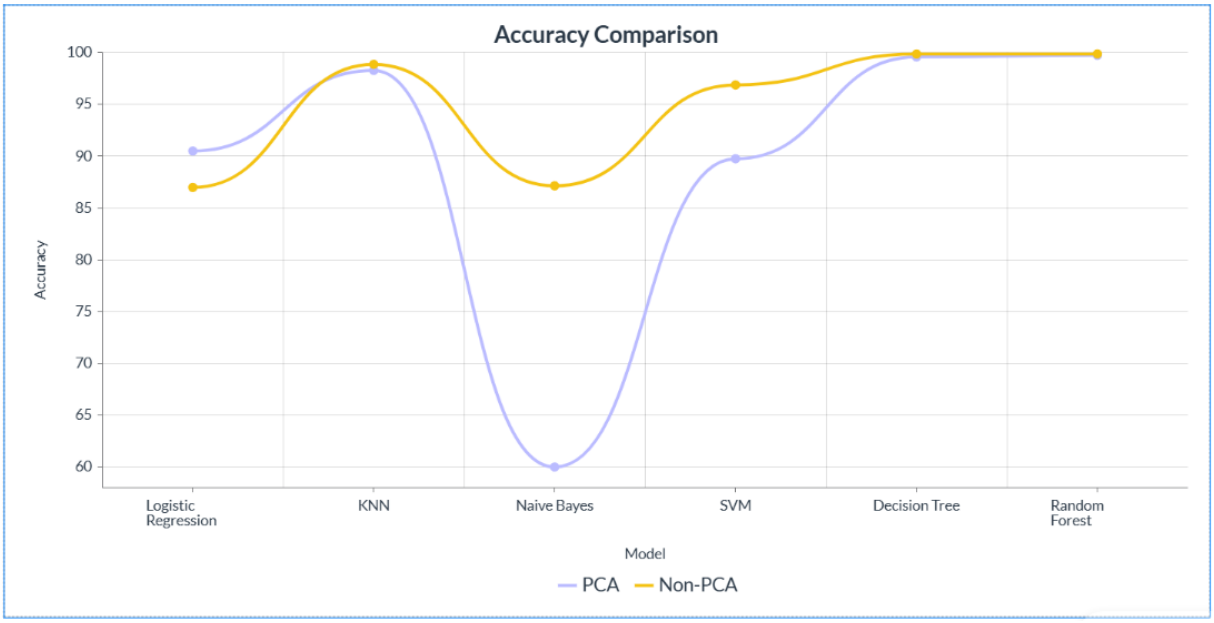
7.2 Confusion Matrix Evaluation

The **CNN-LSTM** model exhibited a particularly strong balance between high true positive rates and low false positive rates. This is crucial in intrusion detection, where false alarms can lead to operational overhead. The model effectively distinguished between **normal** and **attack** traffic, including **low-frequency classes** such as U2R and R2L—two of the most challenging categories due to their rarity.

7.3 Dimensionality Reduction with PCA

To investigate the trade-off between model complexity and efficiency, **Principal Component Analysis (PCA)** was applied to reduce the feature space:

- **Experiment Setup**: PCA reduced input dimensions to 50 components.
- **Model Used for Evaluation**: Random Forest



Findings:

- Performance declined slightly (~1–1.5% drop in accuracy), indicating a modest loss in discriminative information.
- However, **training time and memory usage improved significantly**, making PCA a valuable option for resource-limited systems.

7.4 Model Comparison and Observations

- **Traditional ML Models**:
  - Random Forest showed robust performance but required feature tuning.
  - KNN was computationally heavier and less effective with imbalanced classes.
- **Deep Learning Models**:
  - **CNN and LSTM** models showed strong individual performance.
  - **GRU** served as a faster alternative to LSTM with comparable results.
  - The **CNN-LSTM** hybrid consistently outperformed others by capturing both local spatial patterns and long-term temporal relationships in traffic data.

7.5 Key Takeaways

- The **CNN-LSTM hybrid** model achieved the highest performance and generalization, making it ideal for real-world IDS applications.
- **PCA** proved useful for reducing computational overhead, although it came with a slight trade-off in detection accuracy.
- Deep learning architectures significantly outperformed traditional models in terms of precision and recall, particularly in handling rare and complex attack patterns.
- The ability of models like **LSTM and CNN-LSTM** to learn temporal dependencies is critical in modern IDS systems where attack behavior evolves over time.

8. CONTRIBUTIONS

This project delivers several key advancements in the domain of **network intrusion detection**, leveraging deep learning models and the **NSL-KDD dataset**. The work addresses practical challenges in cybersecurity with a focus on scalability, generalization, and modern deployment readiness.

1. End-to-End Deep Learning Pipeline on NSL-KDD

A comprehensive and modular IDS pipeline was developed for the **NSL-KDD dataset**, covering all essential stages—from data preprocessing (scaling, encoding) to model training and evaluation. The pipeline is reproducible and optimized for experimentation across both classical and deep learning algorithms.

2. High-Performance Hybrid Deep Learning Model

The **CNN-LSTM hybrid model** achieved the **highest classification accuracy (96.08%)**, outperforming standalone models like CNN, GRU, and LSTM. This highlights its capability to effectively capture both spatial and temporal patterns in network traffic, making it a top choice for intrusion detection systems.

3. Evaluation of Dimensionality Reduction

Principal Component Analysis (**PCA**) was applied to explore the trade-off between computational efficiency and detection performance. The experiments revealed that **dimensionality reduction can significantly reduce training time and resource usage**, with only a minor impact on classification accuracy—ideal for deployment in constrained environments.

4. Comparative Study Across Multiple Architectures

A detailed performance benchmark was conducted using both **traditional ML models (KNN, Random Forest)** and **deep learning architectures (CNN, GRU, LSTM, CNN-LSTM)**. All models were evaluated using the same dataset and metrics, providing a clear, side-by-side performance analysis useful for future IDS research and development.

5. Effective Minority Class Detection

Through confusion matrix analysis, the proposed models—particularly **CNN-LSTM**—demonstrated **low false positive rates** and effective detection of **rare attack types** like U2R and R2L, which are typically underrepresented and difficult to classify. This reinforces the system's viability for real-world applications.

6. Use of Refined, Widely Accepted Dataset (NSL-KDD)

Unlike outdated or synthetic datasets, NSL-KDD offers a **clean, de-duplicated, and balanced benchmark** for IDS research. The project’s reliance on this dataset ensures relevance to academic standards and maintains compatibility with prior studies for fair comparison.

7. Foundation for Future Intelligent IDS Systems

The work lays the groundwork for extended research in advanced IDS frameworks, including:

- **Explainable AI (XAI)** for interpretability and auditability of decisions
- **Federated Learning** to support distributed, privacy-preserving intrusion detection
- **Reinforcement Learning** for dynamic and self-adaptive threat response
- **Lightweight deployment** strategies suitable for **IoT and edge environments**

9. CONCLUSION AND FUTURE WORK

In this project, we designed, implemented, and evaluated a range of **machine learning and deep learning models** for detecting network intrusions using the **NSL-KDD dataset**. Among all the models tested, the **CNN-LSTM hybrid** delivered the best performance, achieving an accuracy of **96.08%**, demonstrating a strong capability to learn both spatial and temporal features directly from high-dimensional, encoded network traffic data.

We also explored **Principal Component Analysis (PCA)** as a dimensionality reduction technique. While PCA reduced training time and computational load, the best-performing models—including CNN-LSTM—achieved higher accuracy when trained on the full feature set, highlighting their capacity to extract meaningful patterns without manual feature engineering.

Overall, the results confirm that **deep learning models** outperform traditional machine learning approaches in terms of accuracy, adaptability, and robustness—particularly in handling rare and complex attack types such as U2R and R2L.

To further enhance this research and move toward real-world implementation, the following directions are proposed:

- **Real-Time Intrusion Detection**
  Develop a lightweight and latency-optimized version of the model capable of operating in real-time, suitable for **edge devices** or **critical infrastructure networks**.
- **Cloud-Native IDS Architecture**
  Deploy the trained models in **cloud environments**, enabling **scalable**, **centralized**, and **easily managed intrusion detection** across enterprise systems.
- **User Interface & Alert System**
  Design an interactive **dashboard or alert interface** that allows security analysts to visualize traffic behavior, monitor real-time alerts, and take swift action on detected threats.
- **Explainability and Trust**
  Integrate **Explainable AI (XAI)** methods to improve transparency and trust, especially for enterprise-level adoption and audit compliance.
- **Advanced Learning Paradigms**
  Explore **federated learning**, **online learning**, and **reinforcement learning** to create more **adaptive**, **privacy-aware**, and **self-learning IDS frameworks**.

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