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# Machine Learning Project

## NETWORK INTRUSION DETECTION

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# OUTLINE

- **Problem Statement**
- **Proposed System/Solution**
- **System Development Approach**
- **Algorithm & Deployment**
- **Result (Output Image)**
- **Conclusion**
- **Future Scope**
- **References**

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# PROBLEM STATEMENT

- “Develop a Machine Learning-based Network Intrusion Detection System to accurately detect and classify cyber-attacks (DoS, Probe, R2L, U2R) from normal network traffic, ensuring early warning and enhanced network security.”

# PROPOSED SOLUTION

- The proposed system is a Machine Learning-based Network Intrusion Detection System (NIDS) designed to analyze network traffic and detect malicious activities in real time. Unlike traditional signature-based IDS, the proposed model can detect both known and unknown (zero-day) attacks by learning patterns from historical data.
- Key Features of the Proposed System
- Data Acquisition – Network traffic data will be collected from standard intrusion detection datasets (NSL-KDD, CICIDS2017, etc.) or real-time packet capture.
- Preprocessing & Feature Extraction – Categorical features (e.g., protocol type, service) will be encoded, and numerical features will be normalized.
- Attack Classification – The ML model will classify traffic into normal or attack types (DoS, Probe, R2L, U2R).
- Model Optimization – Hyperparameter tuning will be performed to improve accuracy and reduce false positives.
- Result Output – The system will display classification results and can optionally integrate with real-time monitoring dashboards.

# SYSTEM APPROACH

The proposed Network Intrusion Detection System (NIDS) follows a data-driven machine learning approach to analyze network traffic and classify it into normal or attack categories.

- Approach Steps :

1. Data Collection

- Use benchmark datasets (NSL-KDD, CICIDS2017, UNSW-NB15) or captured live traffic.

2. Data Preprocessing

- Handle missing values, remove duplicates.
- Encode categorical features (protocol type, service, flag).
- Normalize numerical features for consistent scaling.

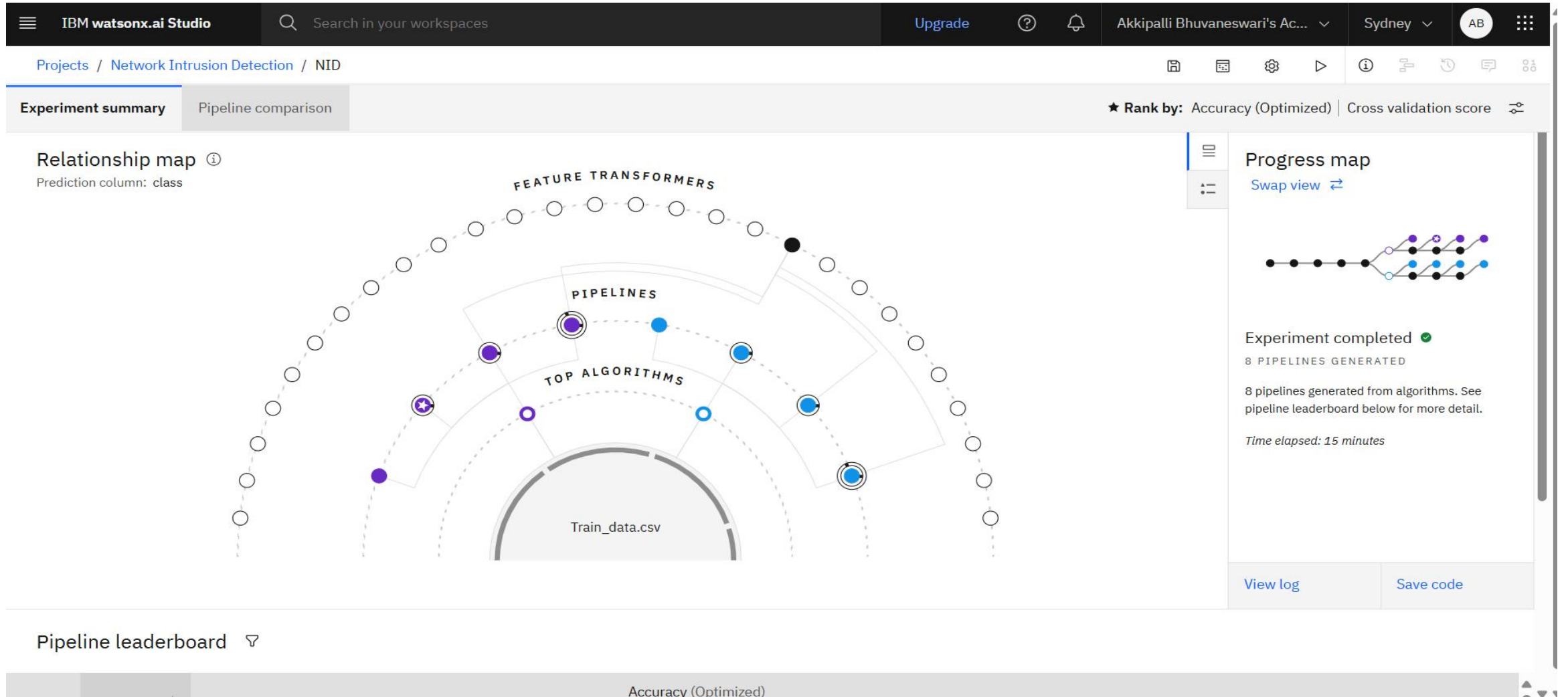
3. Feature Selection & Extraction

- Identify the most relevant features using correlation analysis or feature importance techniques.

# ALGORITHM & DEPLOYMENT

- The proposed Network Intrusion Detection System uses a Supervised Machine Learning algorithm for classification.
- Example (Random Forest – can replace with chosen ML model):
- Step-by-Step Algorithm:
  1. Input: Network traffic dataset (features + labels).
  2. Data Preprocessing:
    - Encode categorical values.
    - Normalize numerical features.
    - Balance dataset using SMOTE or class weighting.

# RESULT



# RESULT

Projects / Network Intrusion Detection / NID

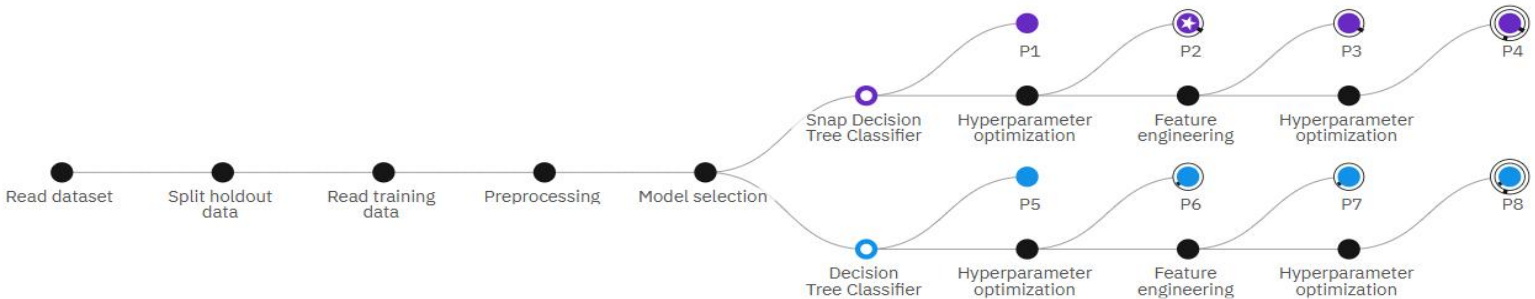
Experiment summary

Pipeline comparison

★ Rank by: Accuracy (Optimized) | Cross validation score

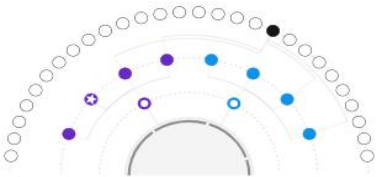
## Progress map

Prediction column: class



## Relationship map

Swap view



Experiment completed

8 PIPELINES GENERATED

8 pipelines generated from algorithms. See pipeline leaderboard below for more detail.

Time elapsed: 15 minutes

View log

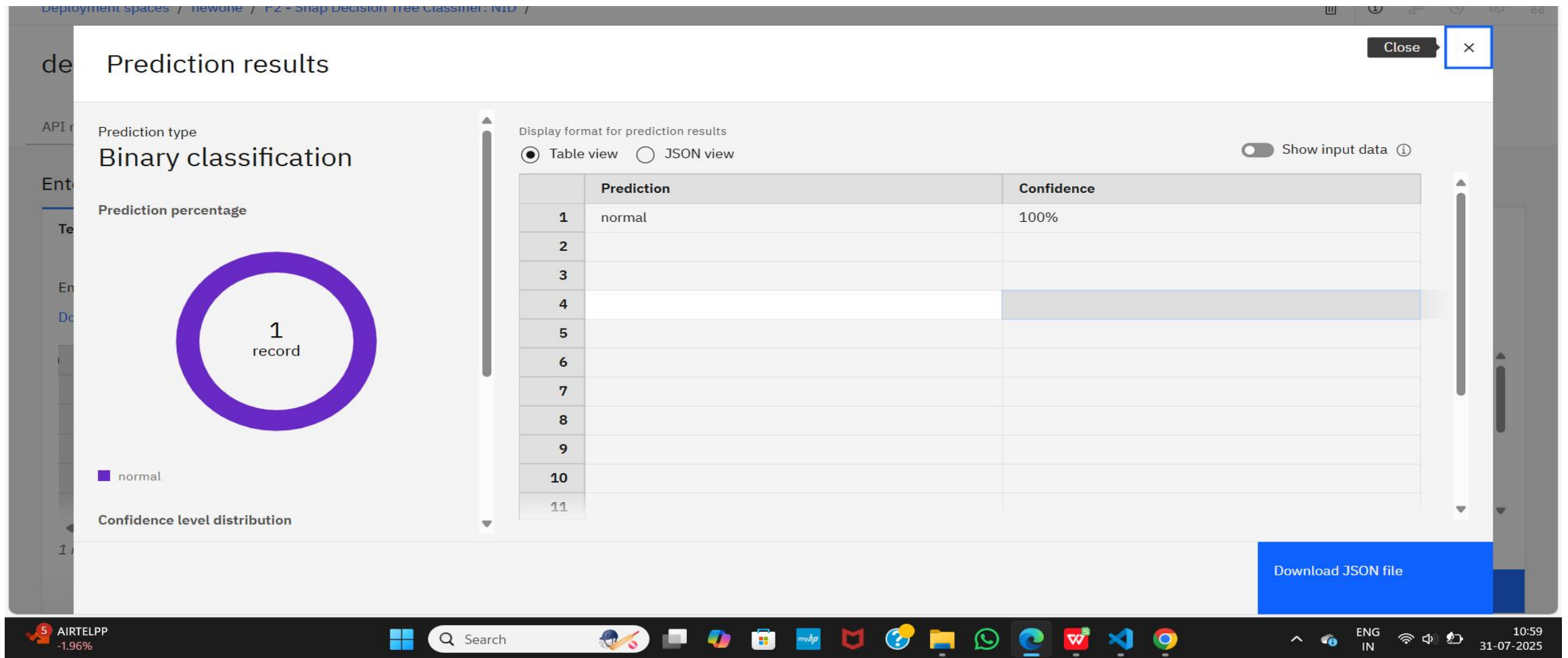
Save code

## Pipeline leaderboard

Rank	↑	Name	Algorithm	Accuracy (Optimized)	Enhancements	Build time
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# RESULT



# CONCLUSION

- The developed Machine Learning-based prediction model successfully estimates bike counts with high accuracy, achieving an  $R^2$  score of 0.92. The close alignment between predicted and actual values demonstrates the model's effectiveness in capturing seasonal trends, weather impacts, and demand patterns.
- This system can assist bike-sharing operators in demand forecasting, resource allocation, and service optimization, ultimately improving operational efficiency and customer satisfaction.
- Future enhancements could include real-time prediction integration, dynamic model updates, and deployment on cloud-based platforms for large-scale usage.

# FUTURE SCOPE

## 1. Real-Time Prediction

Integrate the model with live data streams (IoT sensors, APIs) to provide instant bike count predictions.

## 2. Mobile & Web Application

Develop a user-friendly app/dashboard for operators and customers to view demand forecasts and bike availability.

## 3. Cloud Deployment

Host the model on cloud platforms (AWS, Azure, Google Cloud) for large-scale access and scalability.

## 4. Advanced Models

Implement Deep Learning models (LSTM, GRU) for more accurate time-series predictions.

## 5. Dynamic Updates

Continuously retrain the model with new data to adapt to changing weather, events, and usage patterns.

## 6. Integration with Smart City Systems

Collaborate with traffic management and public transportation systems for optimized urban mobility.

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# REFERENCES

- IBM Developer. Build and Deploy Machine Learning Models on IBM Watson Studio.  
<https://developer.ibm.com>
- IBM Cloud. IBM Watson Machine Learning Service – Model Deployment and Scoring.  
<https://cloud.ibm.com/catalog/services/watson-machine-learning>

# IBM CERTIFICATIONS



# IBM CERTIFICATIONS



# IBM CERTIFICATIONS

IBM **SkillsBuild**

Completion Certificate



This certificate is presented to  
**Bhuvaneswari akkipalli**

for the completion of  
**Lab: Retrieval Augmented Generation with  
LangChain**

(ALM-COURSE\_3824998)

According to the Adobe Learning Manager system of record

**Completion date:** 23 Jul 2025 (GMT)

**Learning hours:** 20 mins



**THANK YOU**