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DEPARTMENT OF CSE-CYBER SECURITY

Major Project

On

Enhanced Botnet Detection in IOT Systems Using a Hybrid Machine Learning Approach

SUBMITTED BY : BATCH - 11

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ABSTRACT

With the rise of IoT, botnet attacks have become increasingly harmful and harder to detect due to evolving attack vectors. This research proposes a stacking model (ACLR) combining ANN, CNN, RNN, and ML models to identify botnet activity using the UNSW-NB15 dataset, which includes nine attack types. The ACLR model achieved 96.98% testing accuracy, ROC-AUC of 0.9934, and PR-AUC of 0.9950, showing strong detection performance. K-fold cross-validation (k = 3, 5, 7, 10) confirmed its robustness, with the best result at k = 5 (97.49%). The model outperformed existing methods, making it a valuable tool for improving cybersecurity against modern botnet threats. This system effectively captures complex attack patterns across diverse traffic data. Its high generalizability makes it suitable for real-world network environments. As cyber threats continue to evolve, the ACLR model offers a scalable and intelligent solution for proactive threat detection.

INTRODUCTION

The rapid growth of the Internet of Things (IoT) has enhanced connectivity across various sectors but also introduced severe security risks. Among these, botnet attacks have emerged as one of the most dangerous threats, exploiting vulnerable IoT devices to perform large-scale malicious activities. Traditional detection methods often struggle to identify such evolving attacks due to their dynamic and complex nature. To overcome these limitations, this project proposes a Hybrid Ensemble Learning Approach (ACLR) for efficient botnet attack detection in IoT systems. The ACLR model combines the strengths of ANN, CNN, RNN, and machine learning algorithms through a stacking mechanism to effectively capture spatial and temporal features of network traffic. Using the UNSW-NB15 dataset, which includes nine attack types, the model demonstrated superior accuracy and robustness compared to existing methods.

By achieving a testing accuracy of 96.98% and validating stability through k-fold cross-validation, the ACLR model proves to be a scalable and intelligent solution for proactive IoT threat detection. This approach contributes significantly to enhancing the overall cybersecurity posture of modern IoT environments.

SOFTWARE REQUIREMENTS

- Operating system : Windows 7 Ultimate
- Coding Language : Python
- Front-End : Python
- Back-End : Django-ORM
- Designing : Html, css, javascript
- Data Base : MySQL (WAMP Server)

HARDWARE REQUIREMENTS

- Processor : Pentium –IV
- RAM : 4 GB (min)
- Hard Disk : 20 GB
- Key Board : Standard Windows
- Mouse : Two or Three Button
- Monitor : SVGA

EXISTING SYSTEM

Botnets are a major cybersecurity threat used for DDoS attacks, data theft, and spam. Traditional detection methods fail to detect encrypted, unknown, and evolving threats. Deep learning models like CNN, LSTM, and hybrid CNN-LSTM have shown high accuracy (up to 99.57%) and cost efficiency in detecting botnet traffic, especially in IoT environments. ANN and BLSTM-RNN models also outperform traditional classifiers like SVM and Naive Bayes. These models enhance detection capabilities while reducing implementation costs by up to 75%.

Disadvantages (Limitations of Existing System):

- Poor Detection of Unknown Botnets – Existing models struggle to identify new or unseen botnet types that differ from known attack patterns.
- Inability to Handle Encrypted Traffic – Encrypted communication hides malicious content, making it difficult for models to analyze and detect threats accurately.
- Lack of Adaptability – Most systems perform well only on specific datasets and fail to adapt to changing IoT environments or evolving attack methods.
- High Implementation and Maintenance Cost – Advanced detection models require high computational resources and frequent updates, increasing cost and complexity.
- Evasion by Attackers – Attackers use advanced evasion techniques to disguise malicious traffic, allowing botnets to bypass traditional detection systems.

PROPOSED SYSTEM

This research introduces a stacking model named ACLR, which integrates Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and traditional Machine Learning (ML) models to achieve efficient and accurate botnet attack detection in IoT environments. The model is designed to classify multiple types of attacks, including DoS, worms, backdoors, fuzzers, reconnaissance, shellcode, exploits, and generic attacks, using a well-preprocessed dataset. Performance evaluation is conducted using key metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, ensuring comprehensive assessment of the model's detection capability.

To validate the model's stability and generalization, k-fold cross-validation is performed with k = 3, 5, 7, and 10, achieving consistent results across all folds. The proposed ACLR framework demonstrates superior detection accuracy and robustness compared to existing methods. By leveraging the combined strengths of deep learning and machine learning algorithms, this hybrid ensemble approach effectively captures complex patterns in IoT network traffic and offers a scalable, intelligent solution for modern cybersecurity challenges.

Advantages

- Combines Multiple Learning Models – Integrates ANN, CNN, RNN, and ML models to enhance detection accuracy and learning capability.
- Effective for a Wide Range of Attacks – Accurately identifies various attack types such as DoS, worms, backdoors, and reconnaissance.
- Comprehensive Performance Evaluation – Assessed using multiple metrics like accuracy, precision, recall, F1-score, and ROC-AUC.
- Robust Validation – Ensures reliability and stability through k-fold cross-validation with multiple values of k.
- Outperforms Existing Models – Achieves higher accuracy and better generalization compared to traditional and standalone deep learning methods.

LITERATURE SURVEY

Reference	Authors	Year	Technique / Model	Dataset / Environment	Key Findings / Outcomes
[1]	N. Koroniotis et al.	2019	Dataset creation	IoT networks	Developed Bot-IoT dataset for network forensic analytics
[2]	O. Ibitoye et al.	2019	DL-based intrusion detection	IoT networks	Analyzed adversarial attacks on deep learning models
[3]	M. Shahhosseini et al.	2022	Deep learning	Raw network traffic	Proposed botnet detection using raw traffic data
[4]	S. Homayoun et al.	2018	Deep learning (BoTShark)	Botnet traffic	Accurate detection of botnet traffic using DL
[5]	M. Ge et al.	2019	Deep learning	IoT networks	Efficient intrusion detection in IoT networks
[6]	M. A. Ferrag et al.	2020	DL comparative study	Multiple datasets	Studied DL approaches for intrusion detection

LITERATURE SURVEY

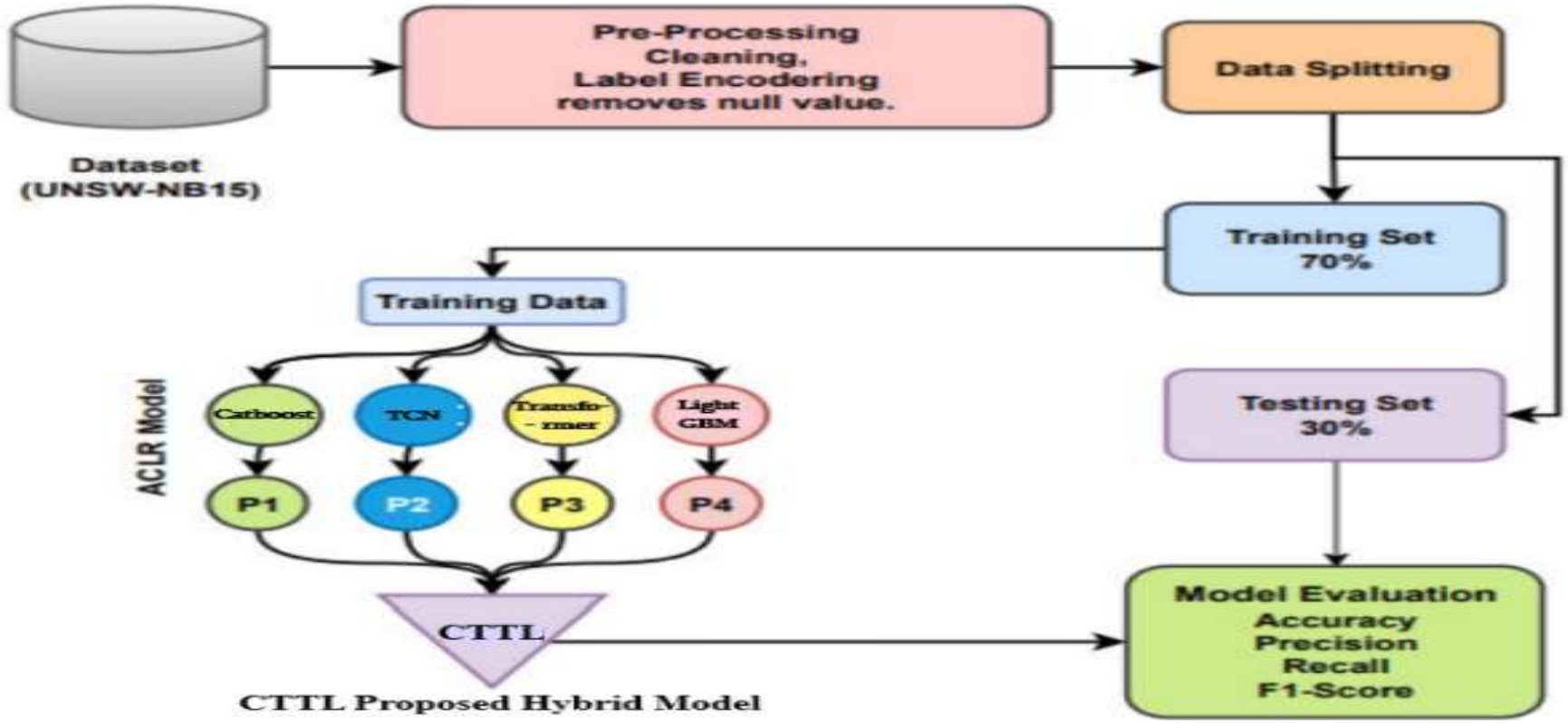
[7]	T. Hasan et al.	2023	Hybrid DL	Industrial IoT	Securing IIoT against botnet attacks
[8]	D. T. Son et al.	2022	Deep learning	IoT networks	Detection of botnet activity using DL techniques
[9]	M. Gandhi, S. Srivatsa	2008	NIDS	Network traffic	Detection and prevention of network attacks
[10]	J. Liu et al.	2019	DL	IoT botnet	Detection of IoT botnets using deep learning
[11]	C. D. McDermott et al.	2018	DL	IoT networks	Botnet detection using deep learning approaches
[12]	S. Sriram et al.	2020	DL (Network flow-based)	IoT botnet traffic	Accurate botnet detection using network flows
[13]	B. Nugraha et al.	2020	DL	Botnet datasets	Performance evaluation of DL-based detection

LITERATURE SURVEY

[14]	P. Karunakaran	2020	DL (DGA classification)	Cybersecurity datasets	Effective classification of DGA domains
[15]	N. Elsayed et al.	2023	Economic DL model	IoT botnet traffic	Efficient botnet detection in IoT networks
[16]	M. A. Haq, M. A. Rahim Khan	2022	DNN	Botnet datasets	Deep neural network-based botnet detection & classification
[17]	I. H. Sarker	2021	DL overview	Various	Comprehensive review of neural network and DL in cybersecurity
[18]	A. A. Ahmed et al.	2022	ANN	CTU-13 dataset	High accuracy (~99%) in botnet attack detection
[19]	I. Letteri et al.	2018	ANN	SDN environment	Effective DDoS detection using ANN
[20]	T. H. H. Aldhyani, H. Alkahtani	2022	CNN-LSTM	Autonomous vehicles IoT	Achieved specificity 93%, F1 score 100% for attack detection

SYSTEM DESIGN

The proposed CTTL Hybrid ACLR model uses the UNSW-NB15 dataset, which is preprocessed and split into 70% training and 30% testing sets. Four base models — CatBoost, TCN, Transformer, and LightGBM — learn different traffic patterns, and their outputs are combined using a CTTL stacking layer. The final model's performance is evaluated using accuracy, precision, recall, and F1-score metrics.

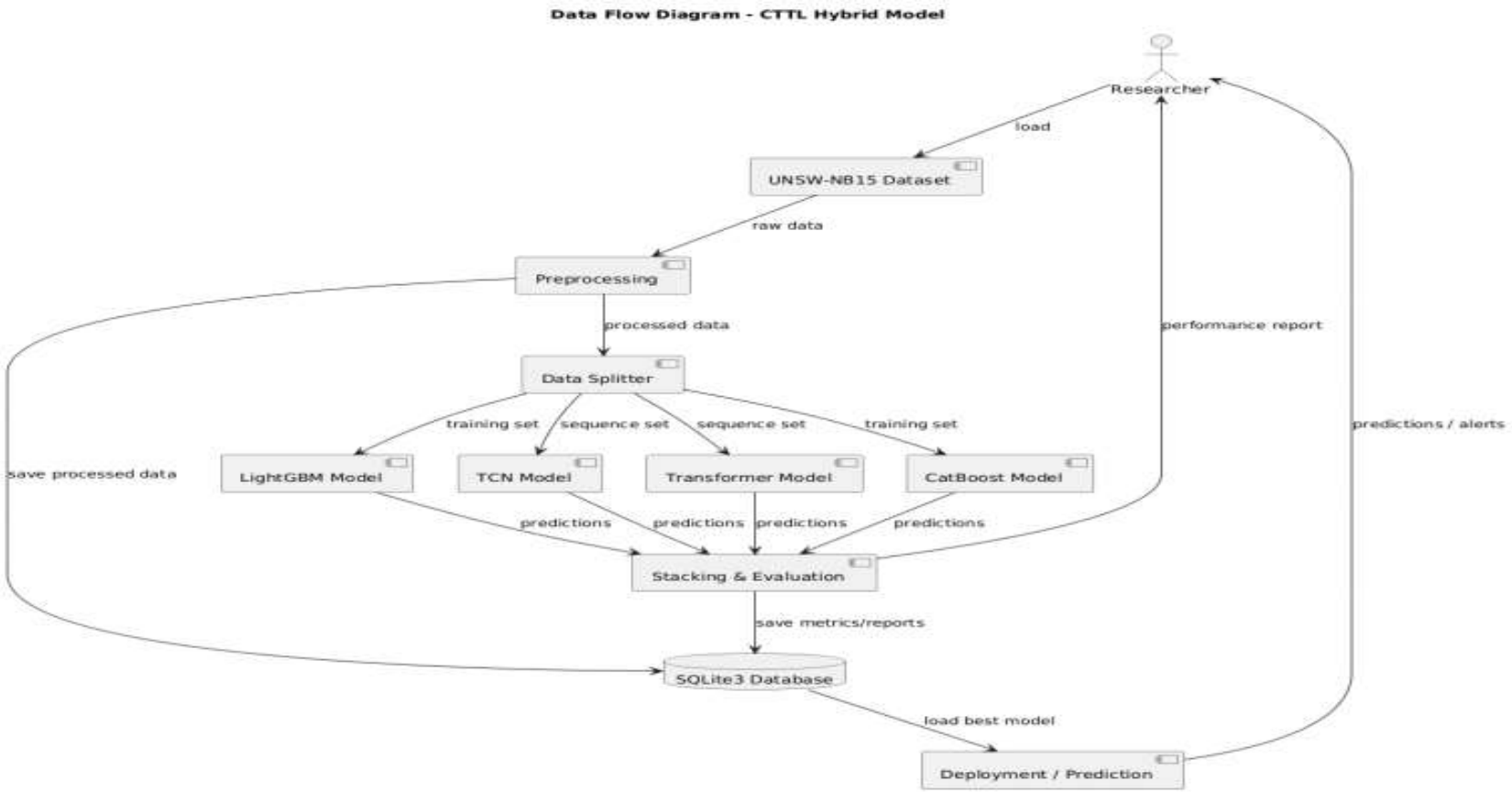


SYSTEM DESIGN

Data Flow Diagram

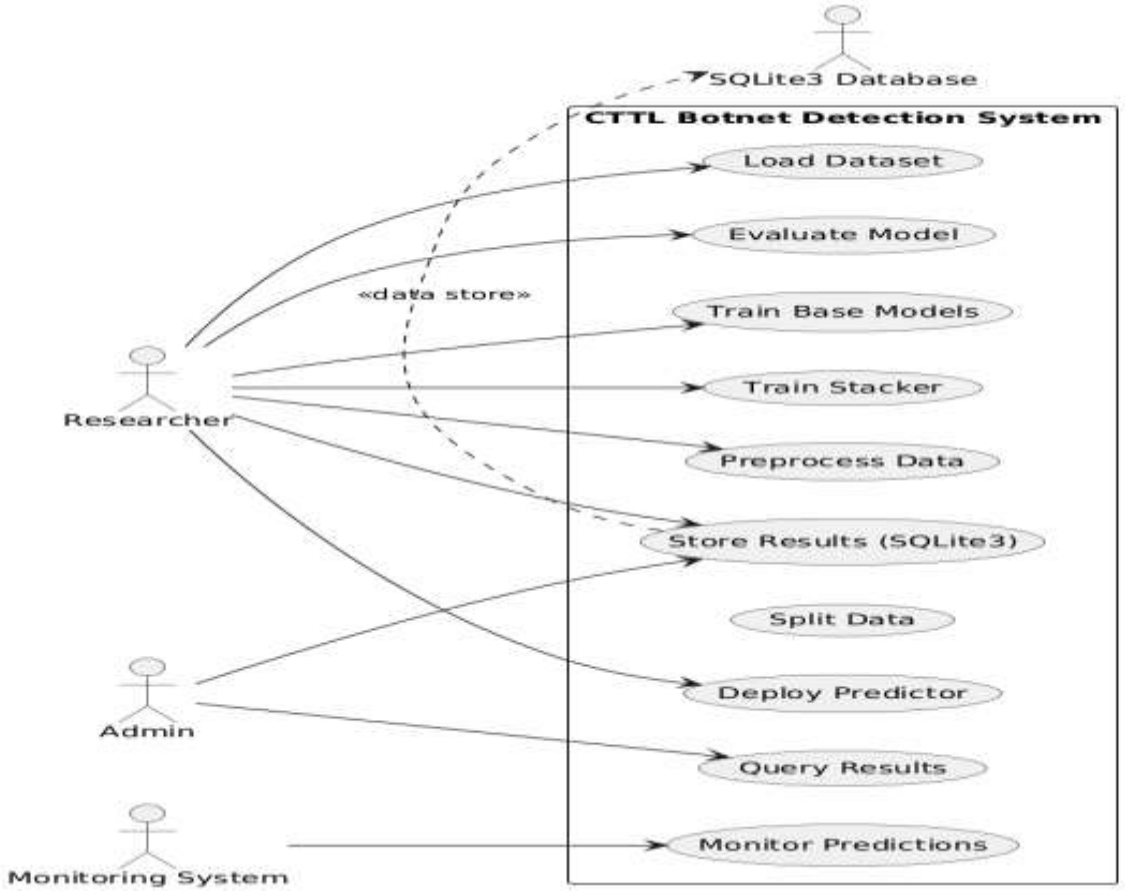
A Data Flow Diagram (DFD) represents how data moves within a system, showing its flow between processes, data stores, and external entities. It illustrates how input data is processed, stored, and transformed into output. External entities act as data sources or destinations, while processes perform operations on data. Data flows indicate the direction of data movement. DFDs provide a clear, high-level view of system functionality through Level 0, Level 1, and Level 2 diagrams.

SYSTEM DESIGN



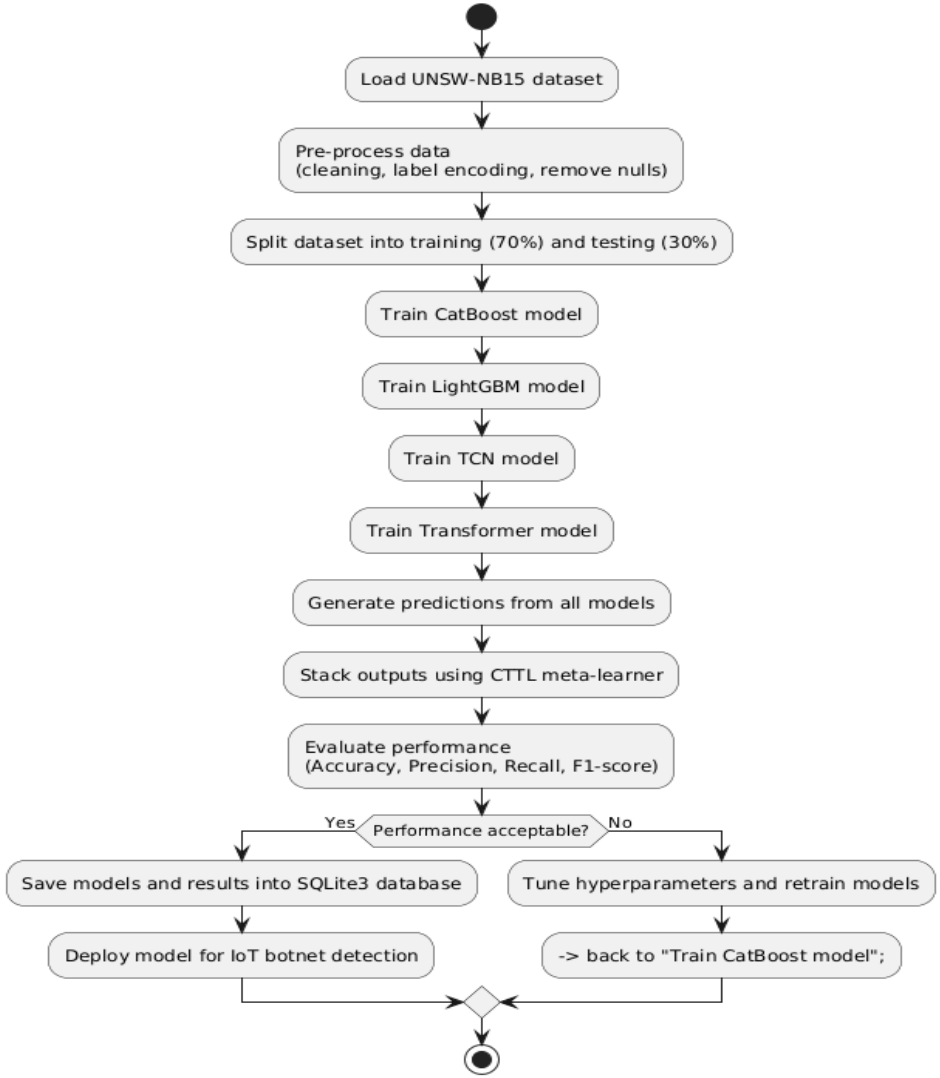
UML DIAGRAMS

Use case Diagram



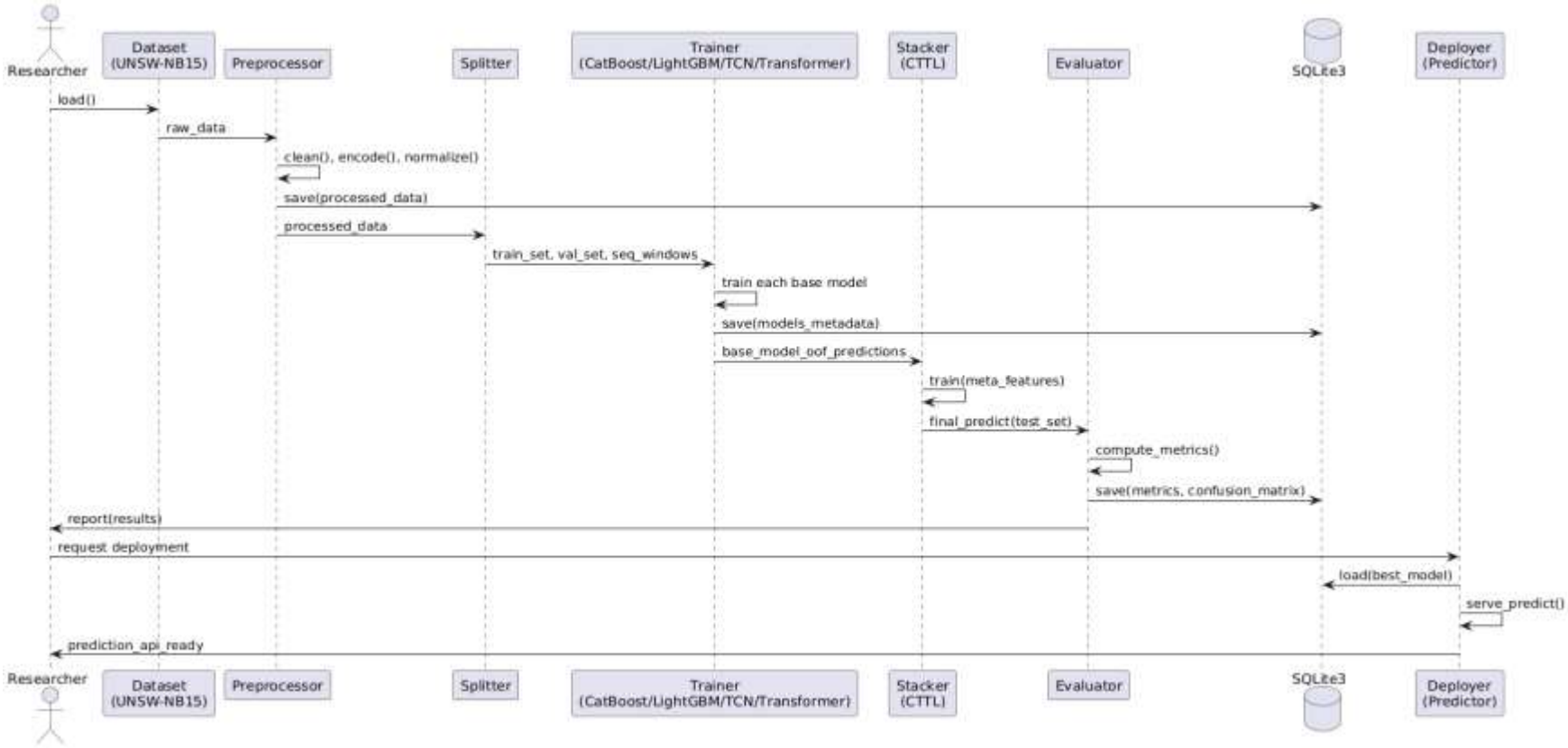
UML DIAGRAMS

Activity Diagram



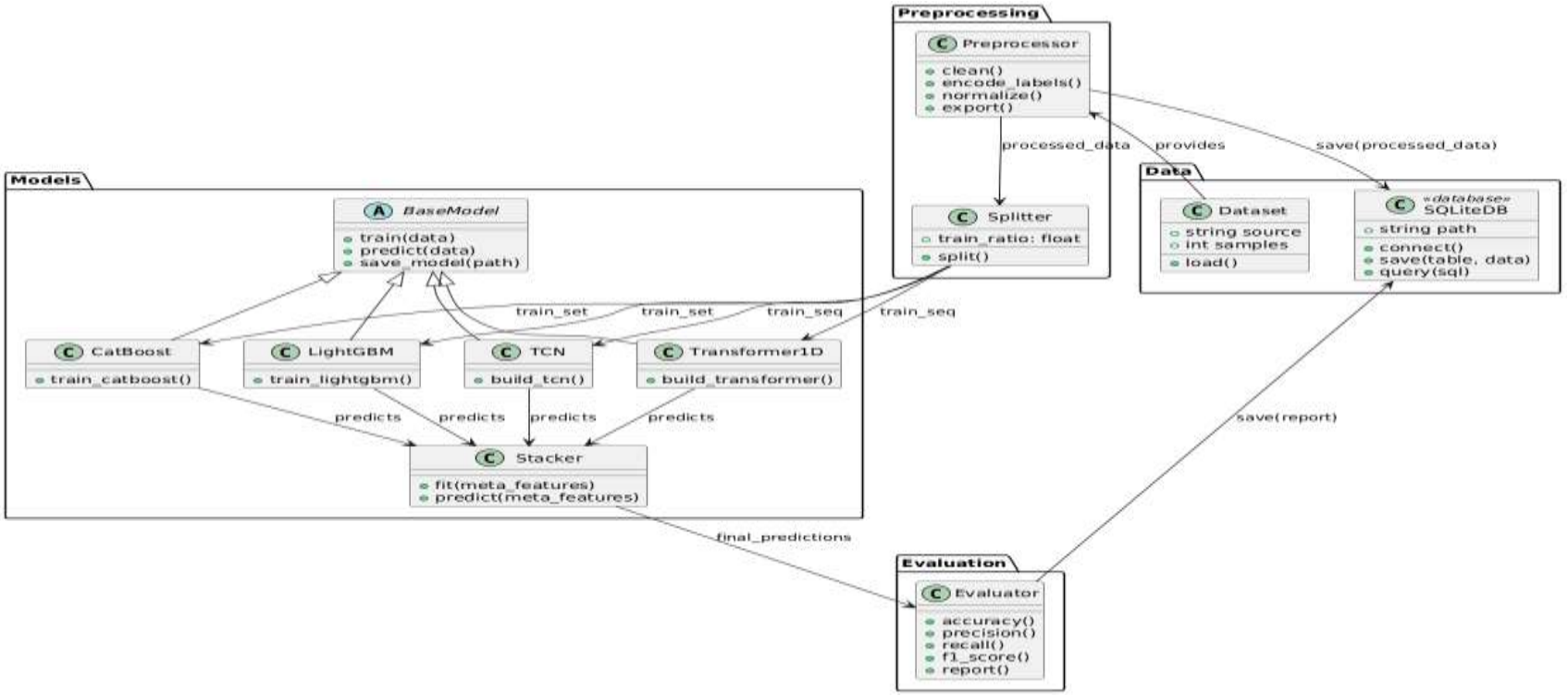
UML DIAGRAMS

Sequence Diagram



UML DIAGRAMS

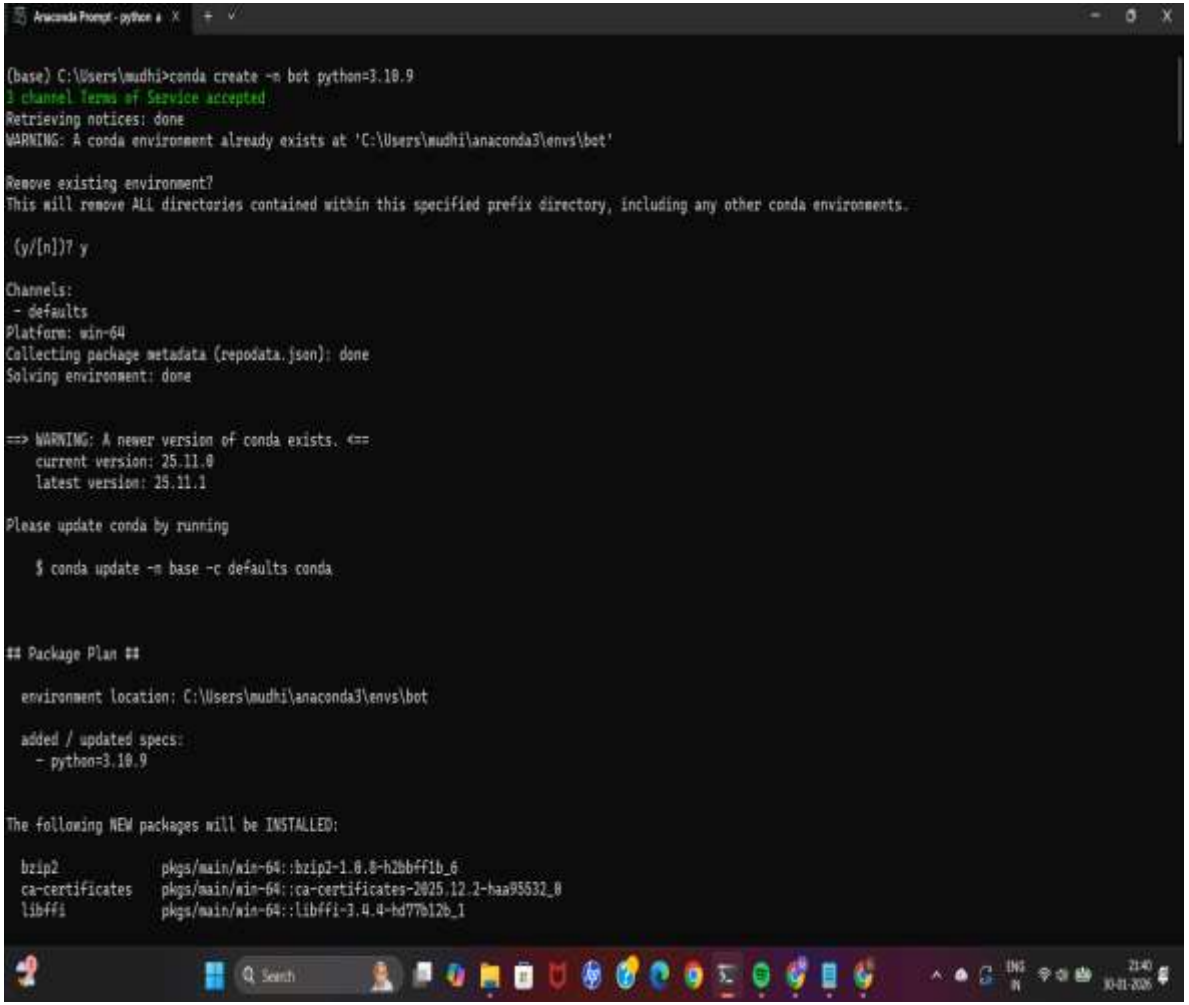
Class Diagram



IMPLEMENTATION

Title: Python Environment and Dependency Setup

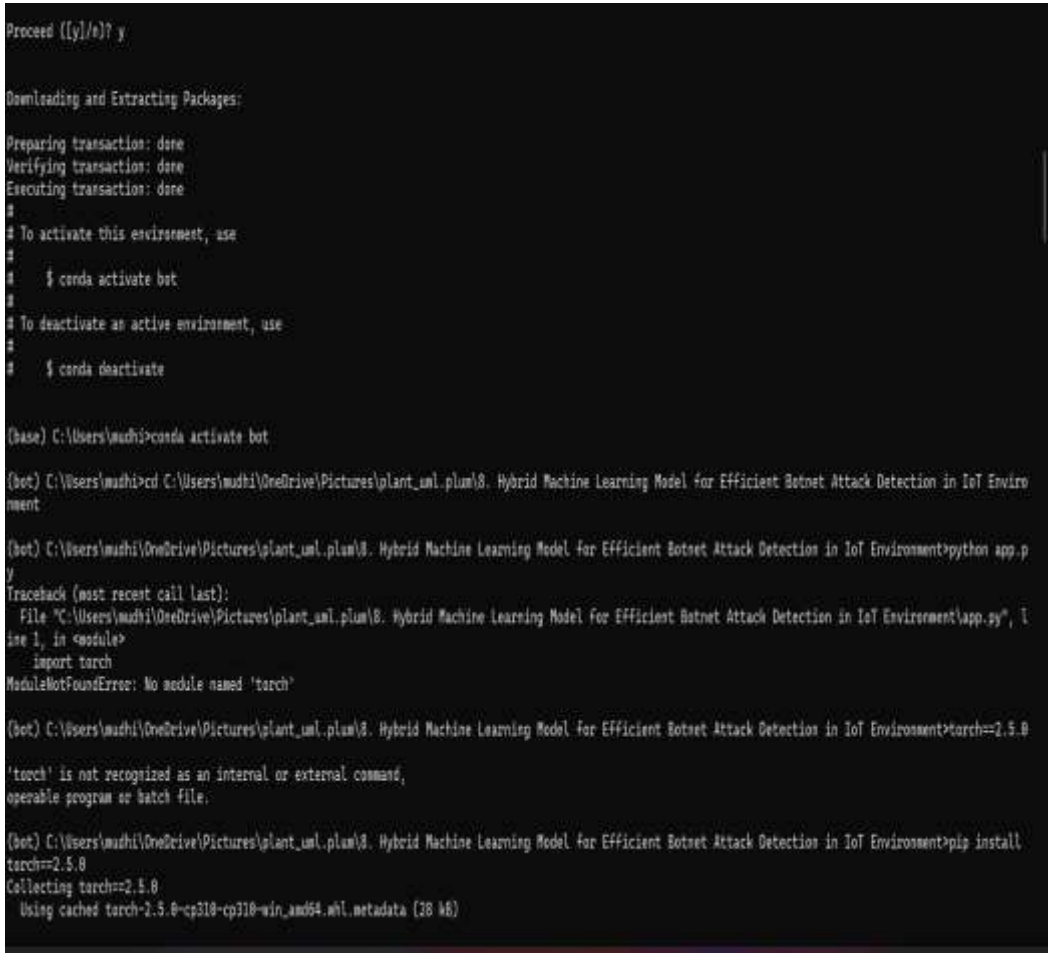
- An isolated **Anaconda virtual environment (bot)** is created to avoid package conflicts.
- Python version **3.10.9** is used for compatibility with machine learning libraries.
- Required packages such as Flask, NumPy, Joblib, Scikit-learn, LightGBM, and PyTorch are installed using `pip`.
- This setup ensures a stable runtime environment for hybrid ML model execution.



IMPLEMENTATION

Title: Web Framework Configuration

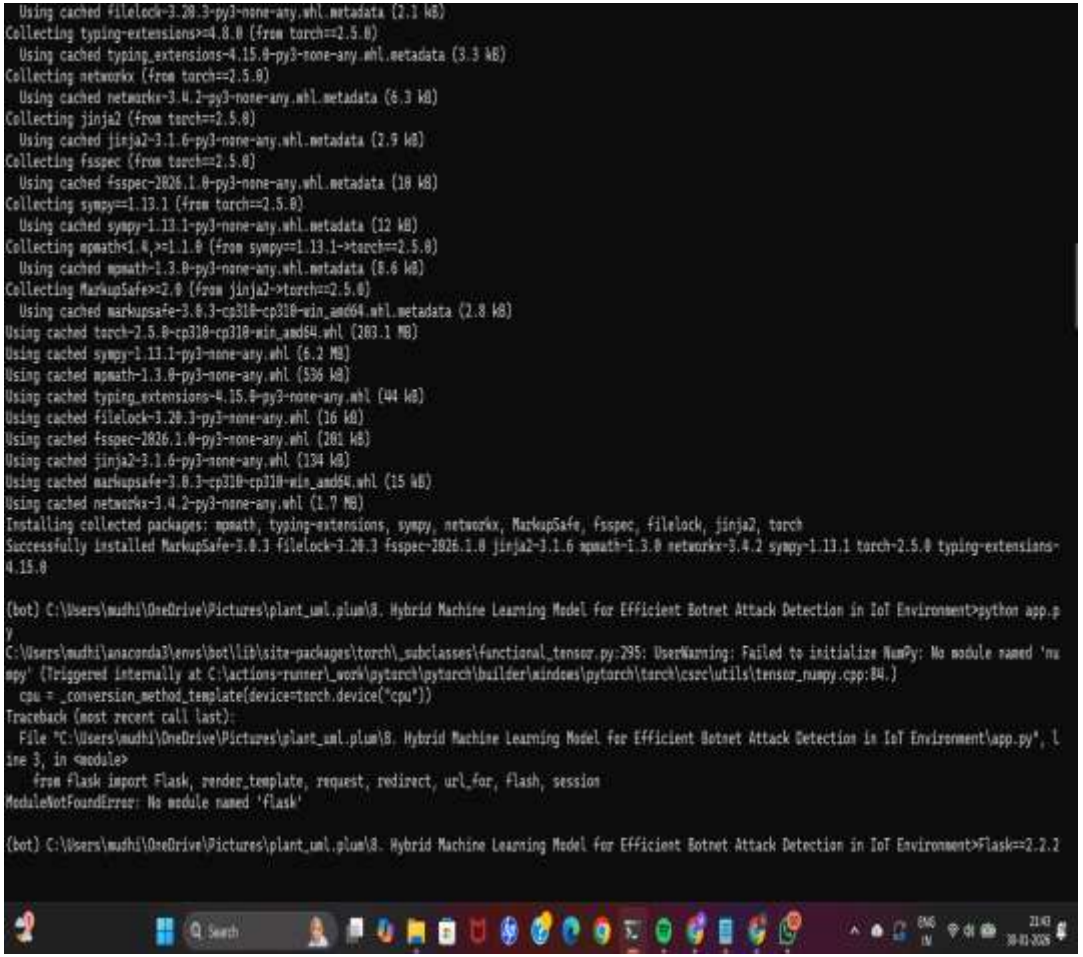
- Flask **(version 2.2.2)** is installed to build the web interface of the system.
- Supporting libraries such as **Werkzeug, Jinja2, Click, and ItsDangerous** are configured.
- Flask acts as the backend server that connects user input with trained ML models.
- The framework enables real-time prediction of botnet attacks through a browser interface.



IMPLEMENTATION

Title: Dependency Conflict Resolution

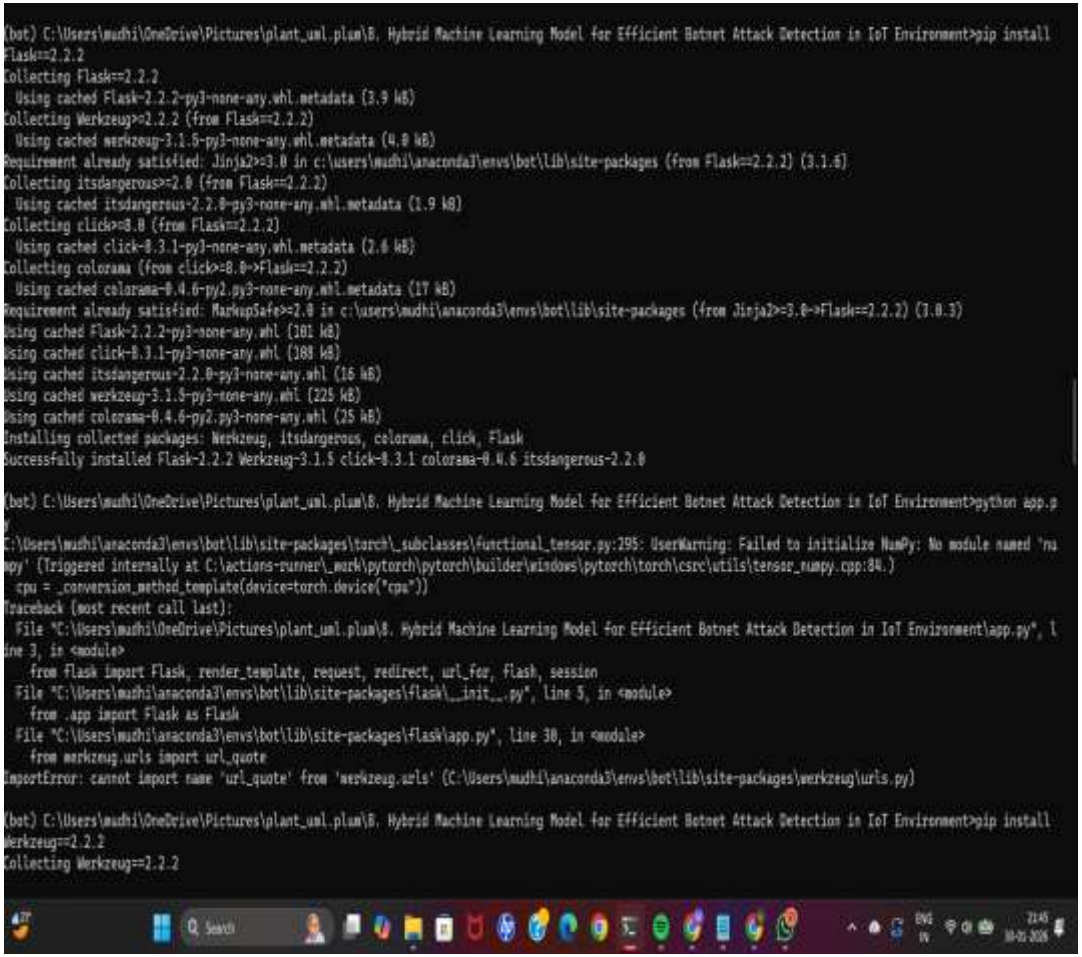
- Initial execution produced errors due to version mismatches between Flask and Werkzeug.
- Werkzeug is downgraded to a compatible version (**2.2.2**) to resolve import errors.
- This step ensures smooth communication between Flask components.
- Proper dependency alignment is critical for stable application execution.



IMPLEMENTATION

Title: ML Model Support Libraries

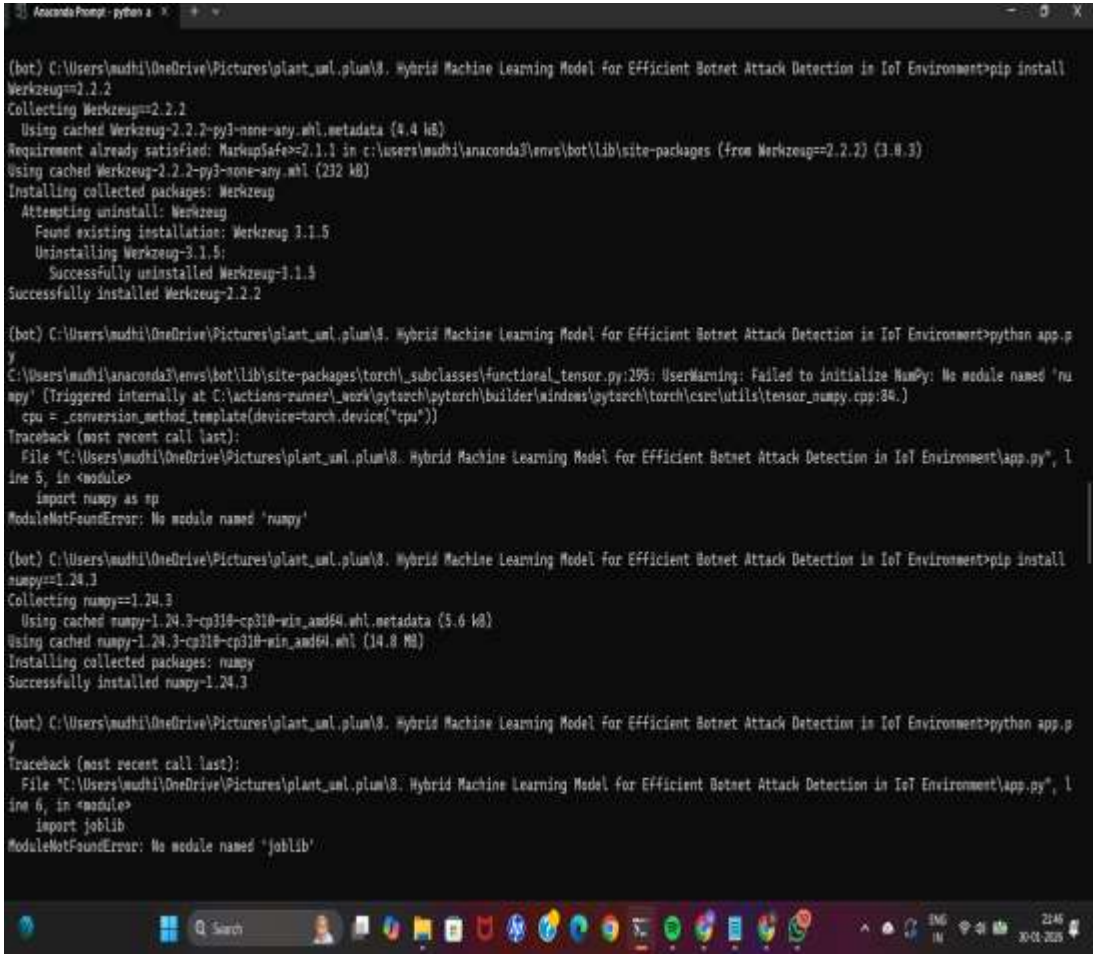
- **Scikit-learn** is installed to support classical machine learning models.
- **Joblib** is used to load trained models and feature scalers (`.sav`, `.pkl` files).
- **LightGBM** is installed to support gradient boosting-based botnet detection.
- These libraries form the traditional ML part of the hybrid approach.



IMPLEMENTATION

Title: PyTorch Model Integration

- **PyTorch (torch 2.5.0)** is installed for deep learning model execution.
- The trained **Attention-based CNN-BiLSTM model** is loaded using `torch.load()`.
- CPU-based inference is used for model prediction.
- This deep learning model captures complex temporal and spatial patterns in IoT traffic.



IMPLEMENTATION

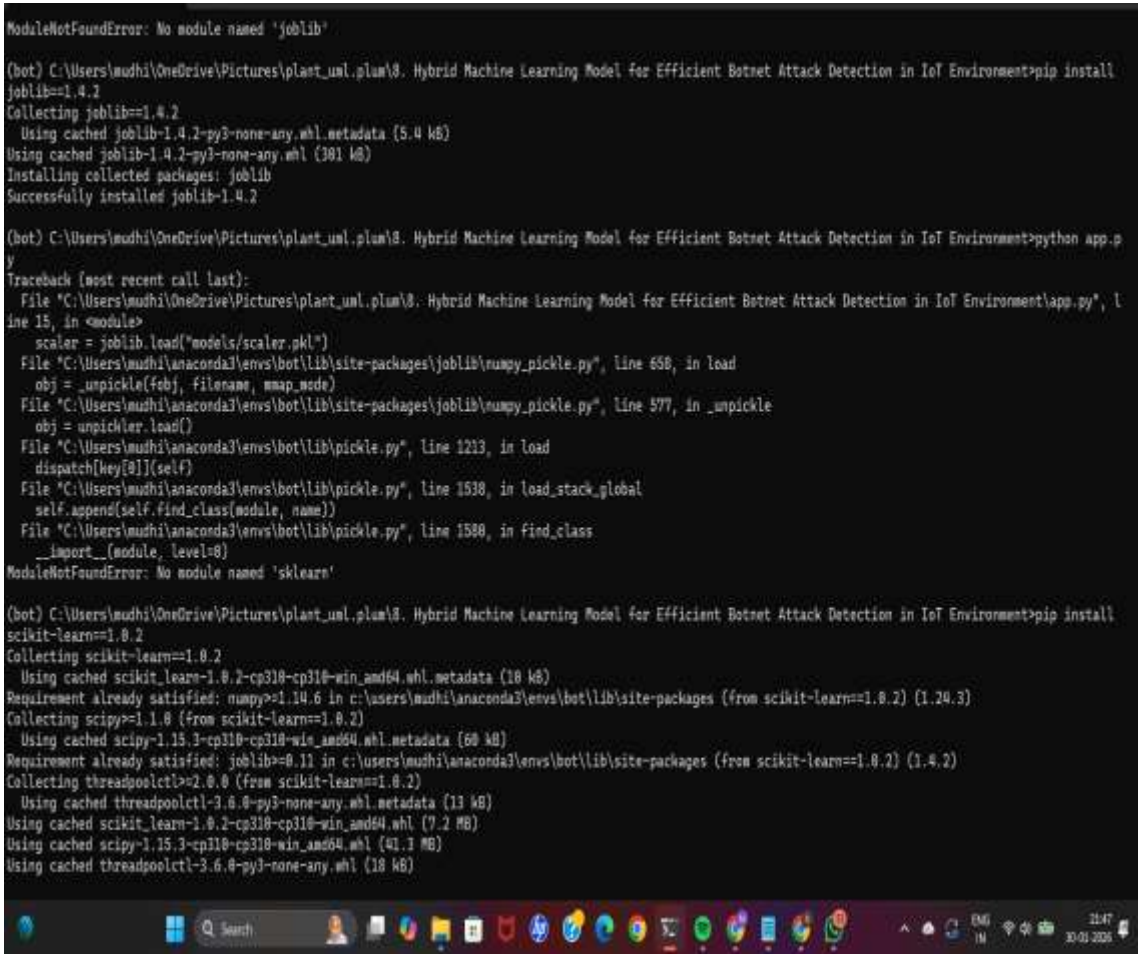
Title: Hybrid Model Loading Process

•Multiple trained models are loaded:

- Classical ML model (`model.sav`)
- Feature scaler (`scaler.pkl`)
- Deep learning model (`att_cnn_bilstm.pth`)

•Models are loaded at application startup to reduce prediction latency.

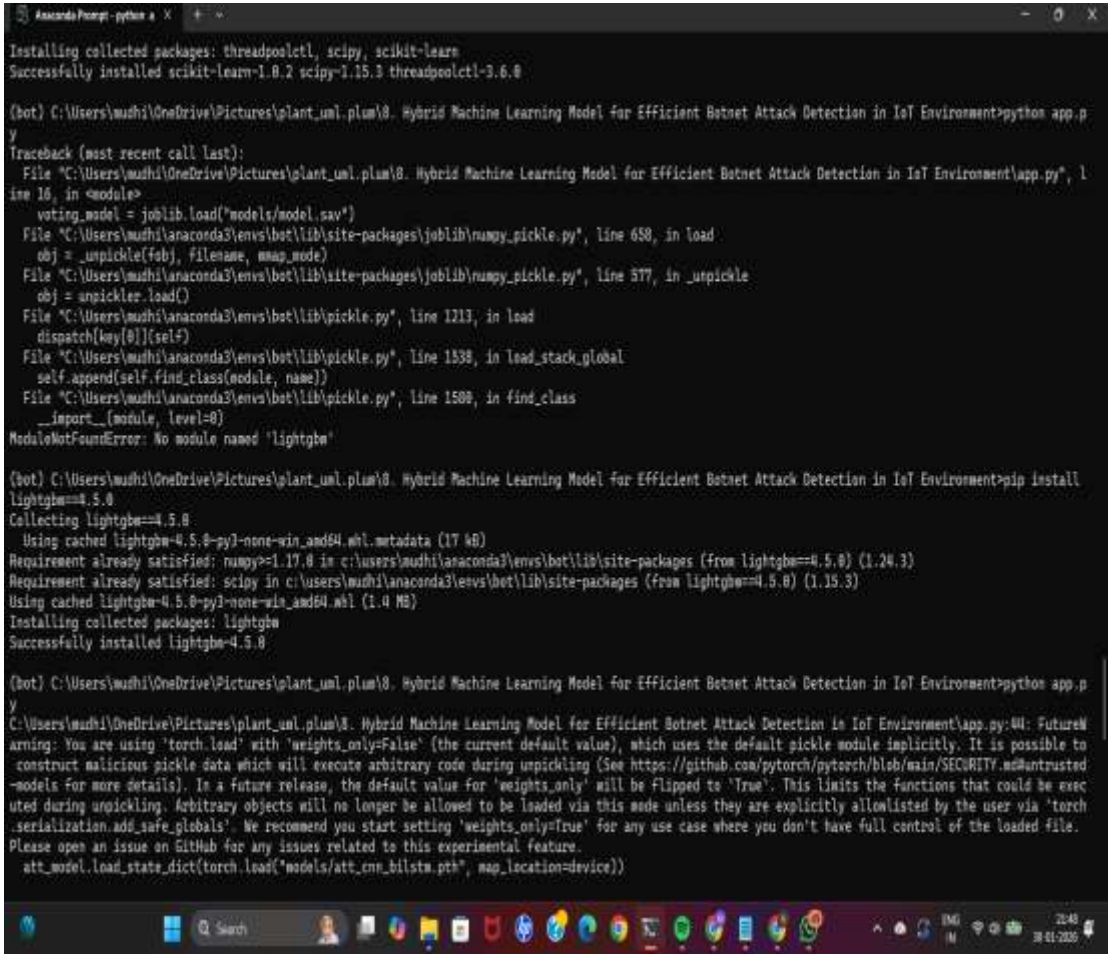
•This enables ensemble-based decision making for botnet detection.



IMPLEMENTATION

Title: Flask Application Execution

- The Flask application is executed using `python app.py`.
- The server starts successfully without runtime errors.
- Flask runs in **development mode** on a local machine.
- The system is now ready to accept input data for prediction.



IMPLEMENTATION

Title: System Running Successfully

- Flask server runs on **http://127.0.0.1:5000**.
- The web interface becomes accessible through a browser.
- Users can input IoT traffic data and receive botnet detection results.
- This confirms successful integration of hybrid ML models with the web application.

IMPLEMENTATION

Title: Project Home Page – Bot-Attack Dashboard

Description:

This slide shows the **home page of the Bot-Attack web application**.

The dashboard introduces the project titled **“Hybrid Machine Learning Model for Efficient Botnet Attack Detection in IoT Environment.”**

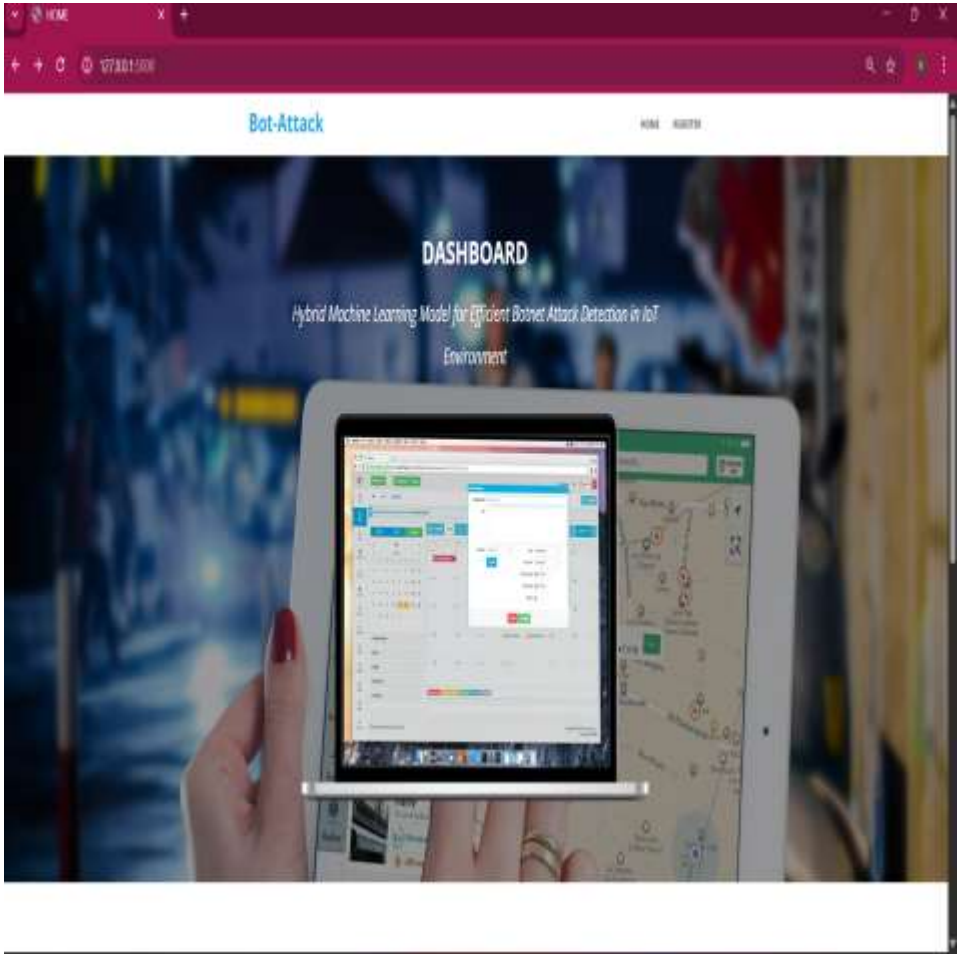
It provides a **user-friendly interface** for accessing the system.

Navigation options such as **Home** and **Register** are available for users.

The dashboard acts as the **entry point** to the botnet detection system.

Purpose:

To present an overview of the system and allow users to start interaction with the application.



IMPLEMENTATION

Title: User Registration Module

Description:

•This slide displays the **Sign-Up page** of the application.

•Users can create an account by entering:

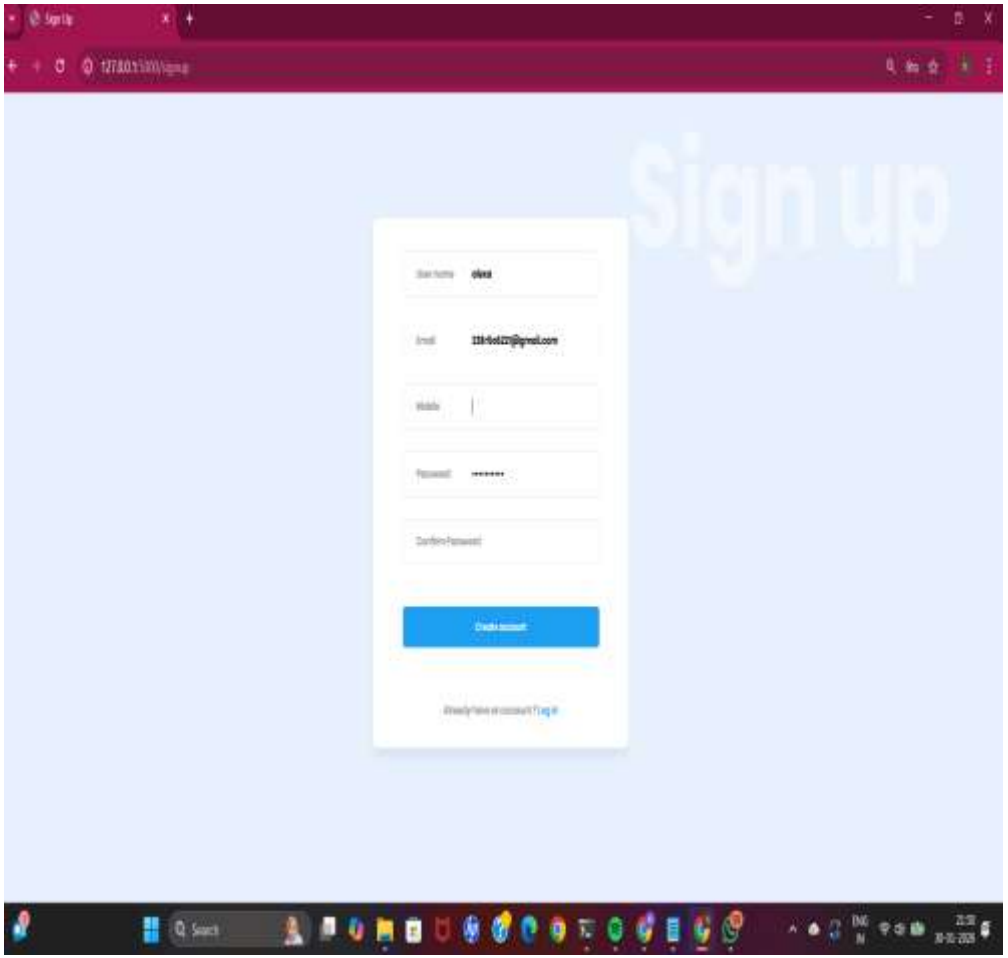
- Username
- Email ID
- Mobile Number
- Password and Confirm Password

•The system validates user input before account creation.

•An option is provided for existing users to **log in directly**.

Purpose:

•To ensure **secure and authenticated access** to the botnet detection system.



IMPLEMENTATION

Title: Network Intrusion Detection System – Input Module

Description:

•This slide shows the **network traffic feature input form**.

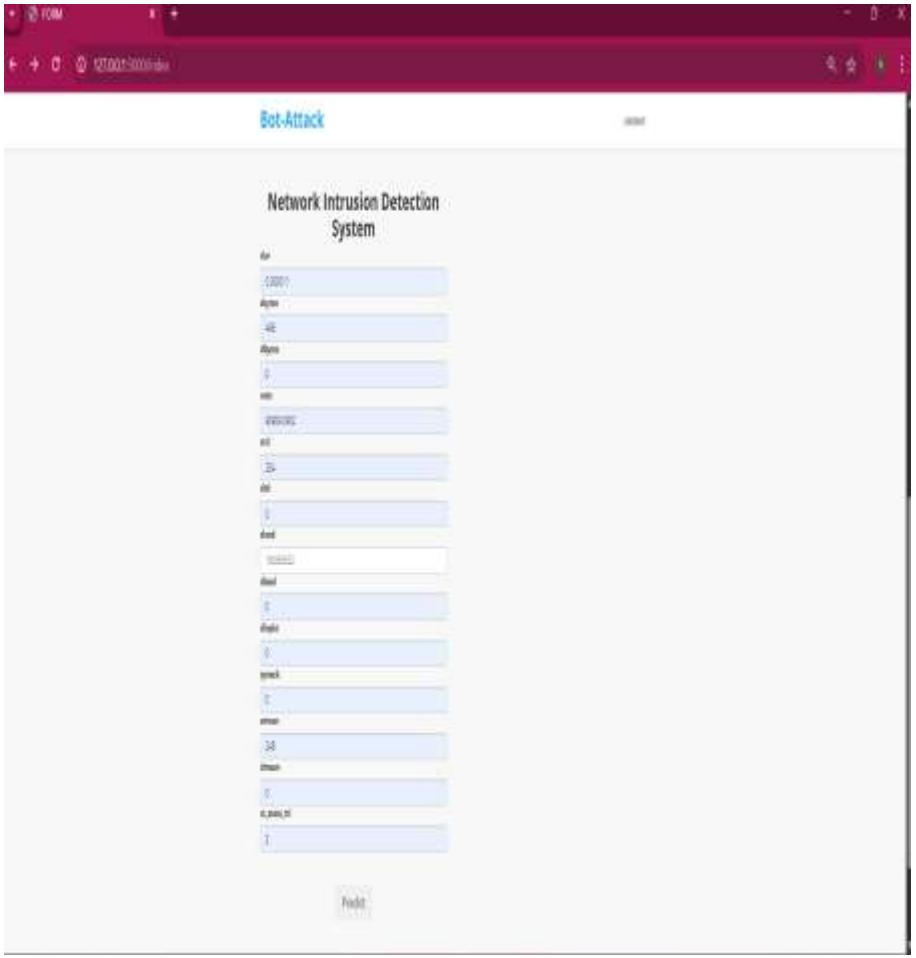
•Users manually enter IoT network parameters such as:

- Duration (dur)
- Source bytes (sbytes)
- Destination bytes (dbytes)
- Rate, TTL values
- Load and packet-related features

•These features represent **real-time IoT network traffic behavior**.

Purpose:

•To collect network traffic data for **botnet attack prediction** using machine learning models.



IMPLEMENTATION

Title: Botnet Attack Detection – Prediction Results

Description:

•This slide displays the **prediction results** after submitting network parameters.

•The system uses a **Hybrid Machine Learning Approach** for detection.

•Two models are applied:

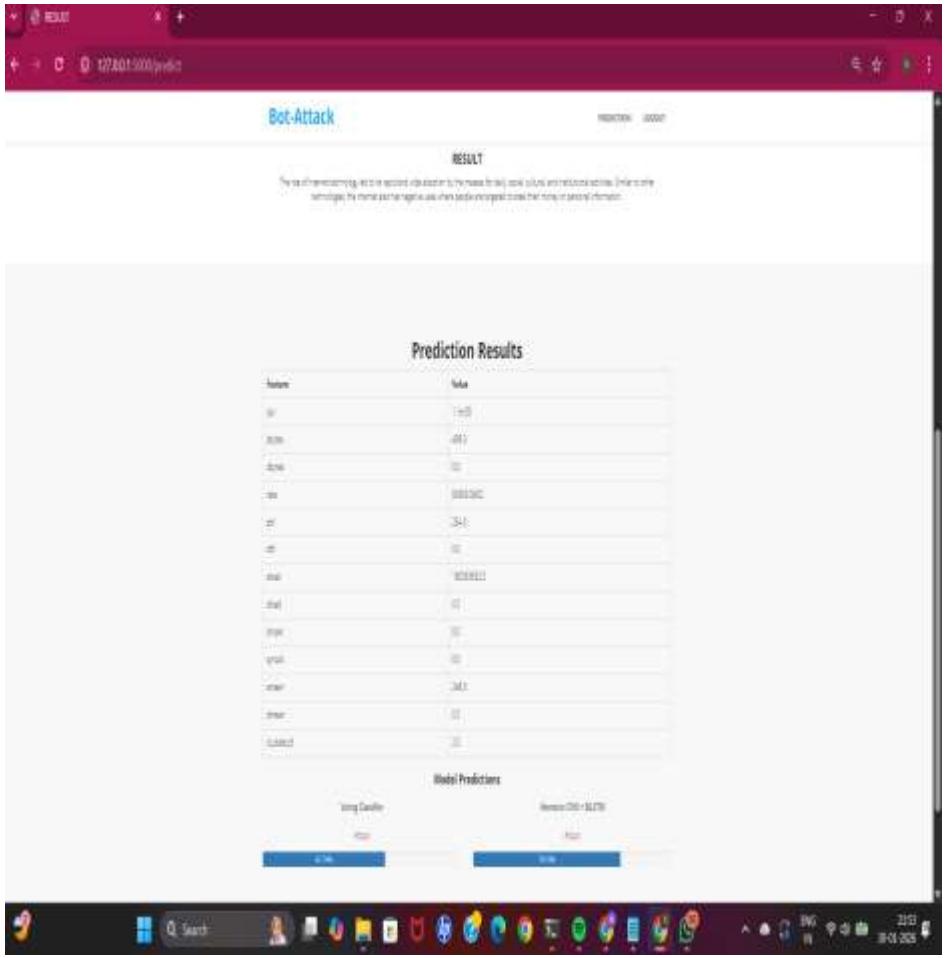
- **Voting Classifier**
- **Attention-based CNN + BiLSTM**

•Both models classify the traffic as **Attack** with confidence percentages.

Purpose:

•To clearly identify whether the given IoT traffic is **Normal or Malicious (Botnet Attack)**.

•To improve detection accuracy using **multiple ML models**.



Conclusion

The proposed Hybrid Ensemble Learning Approach (ACLR) provides an efficient and intelligent solution for botnet attack detection in IoT networks. By integrating CatBoost, TCN, Transformer, and LightGBM models through a CTTL stacking framework, the system effectively captures complex spatial and temporal features of network traffic. Using the UNSW-NB15 dataset, the model achieved high accuracy, precision, and robustness, outperforming existing methods. The results demonstrate that the ACLR model is not only accurate but also scalable and adaptable for real-world IoT environments. This approach contributes significantly to enhancing cybersecurity by enabling early, reliable, and automated detection of evolving botnet threats.

References

[1] N. Koroniotis, N. Moustafa, E. Sitnikova, and B. Turnbull, ‘‘Towards the development of realistic botnet dataset in the Internet of Things for network forensic analytics: Bot-IoT dataset,’’ Future Gener. Comput. Syst., vol. 100, pp. 779–796, Nov. 2019.

[2] O. Ibitoye, O. Shafiq, and A. Matrawy, ‘‘Analyzing adversarial attacks against deep learning for intrusion detection in IoT networks,’’ in Proc. IEEE Global Commun. Conf. (GLOBECOM), Dec. 2019, pp. 1–6.

[3] M. Shahhosseini, H. Mashayekhi, and M. Rezvani, ‘‘A deep learning approach for botnet detection using raw network traffic data,’’ J. Netw. Syst. Manage., vol. 30, no. 3, p. 44, Jul. 2022.

[4] S. Homayoun, M. Ahmadzadeh, S. Hashemi, A. Dehghantanha, and R. Khayami, ‘‘BoTShark: A deep learning approach for botnet traffic detection,’’ in Cyber Threat Intelligence, 2018, pp. 137–153.

[5] M. Ge, X. Fu, N. Syed, Z. Baig, G. Teo, and A. Robles-Kelly, ‘‘Deep learning-based intrusion detection for IoT networks,’’ in Proc. IEEE 24th Pacific Rim Int. Symp. Dependable Comput. (PRDC), Dec. 2019, p. 256.