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Dynamics of Cyber Crime and Awareness: Study of Deep Learning-Based Intrusion Detection in Bihar

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Abstract - This study investigates the dynamics of cybercrime in Bihar, India, and explores a deep learning- based intrusion detection approach tailored to the region's needs. We leverage the CIC-IDS-2018 cybersecurity dataset and employ TabNet, an advanced deep learning model for tabular data, to improve the accuracy of detecting network intrusions. The dataset - consisting of network traffic features and labeled instances of benign and malicious (brute-force attack) behavior -- undergoes thorough preprocessing including cleaning, normalization, and class-balancing to address severe class imbalances. A stratified 5-fold training regime with early stopping is used to train and validate the TabNet model. The results demonstrate nearly perfect detection performance, with the TabNet-based IDS achieving ≈97% accuracy along with high precision, recall, and F1- scores. These findings highlight the effectiveness of deep learning in identifying cyber threats and underscore the importance of enhancing cyber awareness and security measures in Bihar. The study contributes to regional cybersecurity preparedness by providing a high-accuracy intrusion detection framework and emphasizing the need for ongoing cybercrime awareness.

Keywords - Cybercrime Trends; Intrusion Detection System (IDS); Deep Learning; TabNet; Network Security; Bihar (India)

Introduction

Cybersecurity has become a critical concern globally and Bihar, an eastern state of India, is no exception. In recent years, Bihar has witnessed rapid growth in internet connectivity and digital infrastructure, accompanied by a dramatic surge in cybercrime incidents. For instance, reported cybercrime cases in Bihar more than doubled from 1,621 in 2022 to 4,450 in 2023, underscoring the rising vulnerability of citizens and institutions to online threats. Cybercrime incidents in Indian states have surged dramatically, emphasizing the importance of regionalized security frameworks [11]. These threats range from financial fraud (which remains the dominant motive) to identity theft, ransomware, and cyberstalking. The evolving cyber threat landscape in the region poses serious challenges to individuals, businesses, and government agencies, making robust intrusion detection systems (IDS) and heightened cyber awareness an urgent necessity.

Intrusion Detection Systems are designed to monitor network traffic and detect malicious activities or policy violations in real time. Traditional signature-based IDS approaches struggle to keep up with novel and sophisticated attacks. In the context of Bihar's increasing cyber

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incidents, there is a pressing need for intelligent IDS solutions that can learn from data and adapt to emerging threats. Machine learning and deep learning techniques have emerged as powerful tools to enhance IDS performance by automatically identifying patterns of normal and attack traffic. Unlike manual or static methods, learning-based IDS can generalize from historical attack data and recognize subtle anomalies indicative of intrusions.

This paper focuses on a deep learning-based intrusion detection approach tailored for Bihar's cyber threat environment. In particular, we study the application of TabNet[1], an attentive and interpretable deep neural network for tabular data, to detect network intrusions in the CIC-IDS-2018 dataset. TabNet's architecture uses sequential attention to perform feature selection at each decision step, which not only can yield high accuracy but also provides insight into which network features are most important for detection. By leveraging TabNet on real network traffic data, we aim to improve detection rates for cyber attacks prevalent in Bihar while minimizing false alarms. Similarly, Alhassan and Hasan (2023) compared TabNet with XGBoost, demonstrating TabNet's superior accuracy and explainability in network intrusion detection [9].

The primary objectives of this research are two fold: (1) to investigate the current trends and patterns of cybercrime in Bihar, highlighting the need for advanced detection and increased awareness; and (2) to develop and evaluate a deep learning-driven IDS model that can effectively identify intrusions in network traffic data from the region. We specifically concentrate on brute-force attack traffic (a common threat to online services and banking) and normal traffic, as captured in the dataset. The study's findings are intended to enhance cybersecurity efforts in Bihar by providing a high-accuracy detection mechanism and by emphasizing the importance of cyber hygiene and proactive security measures among stakeholders. Ultimately, by raising awareness and deploying state-of-the-art IDS technology, the goal is to bolster the region's cyber resilience against a backdrop of escalating digital threats.

Literature Review

Research into machine learning and deep learning techniques for intrusion detection has been prolific, producing a variety of models that improve detection accuracy and efficiency. In this section, we review several relevant studies on deep learning-based IDS, focusing on their approaches, datasets, and findings:

Shukla et al. (2023) developed UInDeSI4.0, an advanced unsupervised IDS geared towards Industry 4.0 network traffic[2]. Their approach combines feature selection with an Isolation Forest to detect anomalies, enabling the model to accurately identify threats using a minimal subset of features. The proposed system demonstrated high detection performance on the UNSW-NB15 dataset, outperforming traditional IDS solutions and even other deep learning methods in accuracy and efficiency. This highlights the potential of unsupervised learning in scenarios where labeling all attack types is impractical.

Altunay & Albayrak (2023) explored deep learning for IoT network security by comparing CNN, LSTM, and a hybrid CNN+LSTM model for intrusion detection[3]. Using the UNSW-NB15 and X-IIoTID datasets, they evaluated both binary classification (attack vs. normal) and multi-class classification of attacks. Their hybrid model achieved superior results, with detection accuracies of ~92.00% in binary classification and ~92.00% in multi-class settings. These findings suggest that combining convolutional and recurrent networks can effectively capture both spatial and temporal patterns in network traffic, leading to highly accurate IoT intrusion detection. But recent work by Zhang et al. (2024) proposed hybrid CNN–Transformer

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architectures to handle class imbalance, achieving improved precision and recall in large-scale intrusion datasets [7].

Madhu et al. (2023) introduced a device-based intrusion detection system (DIDS) using deep learning to enhance security in large-scale networks[4]. The DIDS model focuses on reducing computational cost and false alarm rates while predicting unknown attacks and issuing early warnings. In their experiments, the model achieved ~97% detection accuracy and demonstrated faster processing compared to conventional methods. This study addressed the research gap of handling unknown or zero-day attacks by using a learning model that generalizes well, thereby improving proactive threat detection.

Pampapathi et al. (2022) proposed a multi-stage intrusion detection model comprising five steps: attack detection, network clustering and cluster-head selection, sensor network initialization, data brokering, and alert generation[5]. Their framework, applied in a wireless sensor network context, outperformed earlier deep learning and ANN-based models. The model achieved an accuracy of 96.12%, exceeding the performance of several popular algorithms in their experiments. The research addressed gaps in coordinating intrusion detection across sensor nodes and demonstrated that a carefully orchestrated multi- step IDS can improve detection in distributed network environments.

Asif et al. (2022) focused on real-time intrusion detection from multiple network sources by proposing the MR-IMID (Multi-Route Intrusion Detection) model[6]. Deep reinforcement learning has also been introduced to adaptively detect novel attacks in IoT environments, showing strong resilience against evolving threats [10]. Their approach anticipates various test conditions by aggregating data from different network segments and uses a predictive algorithm to detect intrusions proactively. The MR-IMID system outperformed state-of-the-art methods, achieving ~97% detection accuracy on training data and ~95% on validation data. This work fills a research gap in integrating multi- source information for intrusion detection and highlights the importance of handling distributed data to reduce blind spots in security monitoring.
Each of these studies contributes to the evolution of IDS technology through deep learning, either by improving accuracy, handling new attack types, or addressing deployment challenges (like IoT constraints or distributed data). Table 1 summarizes key points from the literature, including the methods, identified research gaps, and notable findings or notes from each study.

Authors (Year)	**Method/Model**	**Research Gap**	**Key Findings / Notes**
Shukla et al. (2023)[2]	UInDeSI4.0 -- Unsupervised IDS with feature selection and Isolation Forest on UNSW- NB15 dataset.	Need for efficient unsupervised IDS in Industry 4.0 networks (minimal features for anomaly detection).	High accuracy and efficiency; outperformed traditional IDS and deep models (≈63% better detection rate).
Altunay & Albayrak (2023)[3]	Hybrid CNN + LSTM model for IoT intrusion detection (binary & multi-class) on UNSW-NB15, X-IIoTID.	Lack of clarity on optimal DL architecture for IoT IDS and handling multi-class intrusion detection	Hybrid CNN-LSTM outperforms standalone models, achieving ~92.00% accuracy in multi-class IoT intrusion detection.

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		in IIoT environments.	
Madhu et al. (2023)[4]	DIDS -- Device-based deep learning IDS aimed at large networks; emphasizes early warning of unknown attacks.	Reducing false alarms and computational cost in IDS, and detecting zero-day attacks in huge network traffic.	~97% detection accuracy with lower false alarm rate; provided timely alerts for novel attacks. Improved speed over conventional methods.
Pampapathi et al. (2022)[5]	Five-stage IDS (attack detection, clustering, etc.) for sensor networks; integrates Deep Learning/ANN components.	Need for multi-step, cooperative IDS for wireless sensor and IoT networks to improve detection accuracy and reliability.	Achieved 96.12% accuracy, surpassing popular prior algorithms. Demonstrated that multi-stage hybrid approaches can enhance IDS performance in sensor networks.
Asif et al. (2022)[6]	MR-IMID -- Multi-Route IDS aggregating real-time data from multiple sources; predictive model for intrusion.	Integration of multiple network data sources for intrusion detection and reducing surprise from unseen conditions.	Outperformed state-of-art methods with 97% training and 95% validation accuracy. Showed efficacy of multi-source data fusion in IDS.

Table 1. Summary of related studies on deep learning-based Intrusion Detection Systems. Each study addresses specific gaps, from unsupervised learning for novel attacks to hybrid models for IoT security, and reports significant improvements in intrusion detection accuracy.

Methodology –

The research methodology is designed to develop a high-accuracy intrusion detection model using deep learning, and to evaluate its performance on real network data relevant to Bihar's cyber threat landscape. The approach can be outlined in several stages: (1) Data preparation, including dataset selection and preprocessing; (2) Model configuration and training, involving the TabNet deep learning model with cross- validation; and (3) Evaluation and analysis of results through performance metrics and feature importance.

Dataset and Preprocessing

We utilize the CIC-IDS-2018 dataset, a comprehensive benchmark dataset for network intrusion detection research. This dataset contains network traffic flow records with 78 features capturing a range of traffic attributes -- for example, protocol type (e.g., TCP/UDP), source/destination port numbers, flow durations, packet counts and byte totals in forward/backward directions, statistical measures of packet lengths, flow rates (bytes/packets per second), and various TCP flags and status counts. Each record in the dataset is labeled as either benign or belonging to a specific attack type (the Label column).

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For this study, we focus on a subset of CIC-IDS-2018 that highlights brute-force attack traffic (FTP and SSH brute-force attempts) alongside normal traffic. This subset was chosen because such attacks (e.g., credential guessing) are common and relevant to the types of cyber fraud observed in Bihar (such as unauthorized access to systems, ATM frauds, etc.). The raw data file for the selected subset contained approximately 199,859 records with 79 columns (78 features + 1 label). A brief examination of the class distribution revealed a severe imbalance: out of ~199k total samples, about 179,244 were labeled as "FTP-BruteForce" attacks, 20,348 as "SSH-Bruteforce" attacks, and only 266 as "Benign" normal traffic. In other words, over 92.00% of the records represented malicious traffic, whereas legitimate traffic constituted only a tiny fraction. This imbalance reflects reality in collected intrusion data (where attacks were heavily sampled), but it poses a challenge for model training -- a naive classifier could achieve high accuracy by always predicting the majority class. Therefore, careful preprocessing and balancing were necessary to train an effective IDS model.

The data preprocessing pipeline included the following steps to ensure a clean and learnable dataset:

- Handling Missing Values: The dataset had some undefined or infinite values (e.g., due to division by zero in flow calculations). We replaced any infinite values with NaN and then removed records with missing values. A total of 78 missing entries were found and dropped to prevent errors.
- Removing Duplicates: A significant number of duplicate records (exact duplicates of network flows) were present -- likely due to how the data was aggregated or logged. Using Pandas, we detected 117,437 duplicate entries in the raw data and removed them. Eliminating these duplicates reduced the dataset size and ensured that the model would not bias toward repeated samples. After this step, the unique record count was substantially lower (on the order of 80,000 records), which is more manageable and free of redundancy.
- Outlier Detection: To further enhance data quality, we incorporated an outlier detection algorithm to identify and filter potential outliers in the feature space. This helps in removing noise that might otherwise mislead the learning process. (In practice, only a small percentage of flows were isolated as outliers and were excluded.) Feature Scaling: We applied feature normalization to put all numeric features on a comparable scale. Most features in CIC-IDS-2018 are counts or rates that vary in magnitude; for instance, packet counts can range from 0 to thousands, while some rate features are fractional. Using either standardization (zero-mean, unit- variance scaling) or min-max normalization, we transformed features to ensure that no single feature dominated due to scale. This is important for TabNet and many machine learning models to stabilize training and accelerate convergence.
- Class Balancing: Given the extreme class imbalance (Benign traffic being less than 0.2% of data), we employed oversampling to balance the classes. We generated additional synthetic samples for the minority class (Benign) using oversampling techniques. Oversampling the minority class to a reasonable fraction of the majority helps the model learn decision boundaries for rare classes rather than treating them as noise.

Additionally, we experimented with class weight adjustments in the loss function so that misclassifying a Benign instance would be penalized more than misclassifying an abundant attack instance. This combination of oversampling and weighted loss mitigates bias toward the majority class and maintains data integrity during training.

After preprocessing, the dataset was split into training and testing sets. We used an 80/20 split (stratified by class) resulting in a training set of about ~160k samples and a test set of ~40k

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samples. The stratification ensured that the tiny Benign class was represented in both training and test splits. The training data (after oversampling) was used for model training and cross-validation, while the hold-out test set (not oversampled) was kept for final performance evaluation to assess generalization.

TabNet Model and Training Configuration

For our deep learning model, we chose TabNet -- an attentive, interpretable tabular data learning architecture proposed by Arik and Pfister (2019)[1]. TabNet is specifically designed for tabular datasets and uses a sequential attention mechanism to select which features to process at each step of its decision-making. This allows the model to focus on the most relevant features and achieve a form of built-in feature selection, leading to both high accuracy and interpretability in terms of feature importance. Another advantage of TabNet is that it can naturally handle unnormalized numerical data and does not require extensive feature engineering, which is suitable for our wide range of network traffic features.

We implemented TabNet using the PyTorch TabNet library. The model was configured with optimized hyperparameters based on prior experimentation and recommendations:

- Network architecture: We set the feature transformer and attentive transformer dimensions as n_d = 128 and n_a = 128, respectively, which determine the width of the network's decision and attention layers. The model was allowed n_steps = 7 sequential decision steps (akin to 7 decision tree-like splits), enabling it to refine its attention over multiple rounds.
- Learning rate and optimizer: We used the Adam optimizer for gradient descent with a moderate initial learning rate, along with a StepLR scheduler (decay factor $\gamma = 0.5$ every certain number of epochs) to reduce the learning rate and fine-tune convergence as training progressed.
- Regularization: To prevent overfitting, TabNet's built-in sparse attention mechanism acts as regularization by pruning unnecessary feature usage. Additionally, we employed early stopping and a limited number of training epochs as described below.
- Training protocol: We trained the model using stratified 5-fold cross-validation. The training set was further divided into 5 folds, and in each fold, 80% of the data was used for training and 20% for validation. This approach ensures robust evaluation across multiple data splits and helps in utilizing the full training set for learning patterns. For each fold, training continued for up to 150 epochs with a batch size of 2048 samples. We enabled an early stopping criterion with patience of 15 epochs; if the validation accuracy did not improve for 15 consecutive epochs, training for that fold was halted to avoid overfitting.
- Class weights: We set TabNet's loss function (cross-entropy) to incorporate class weights inversely proportional to class frequencies (higher weight for Benign, lower for attack classes). This compliments our oversampling strategy to ensure the model gives due importance to minority class predictions.
- Each fold's model was trained on a GPU (NVIDIA T4) for efficient computation. During training, we monitored the validation accuracy. Thanks to TabNet's architecture and our preprocessing, the model converged quickly.
- For instance, in Fold 1, the validation accuracy jumped above 98% within the first epoch and exceeded 97.00% by epoch 6, after which early stopping was triggered. Similar behavior was observed in other folds, often reaching a best validation accuracy of ~97.00% before stopping. This indicated the model was learning the distinctions between attack and benign traffic extremely well. TabNet continues to gain traction for its interpretable feature attention; recent studies report success in anomaly detection within financial and network datasets [12].

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- After cross-validation, we computed out-of-fold predictions for the entire training set (each training sample's prediction from the fold where it was in validation). This allowed us to evaluate performance on the training data without bias. Finally, we trained a final TabNet model on the entire cleansed training set (using the same hyperparameters) to serve as the production IDS model. The final model was then tested on the untouched 20% test set for an unbiased evaluation of real-world performance.

Data Collection

Data collection for this research was centered on the CIC-IDS-2018 dataset, which is a widely-used benchmark compiled by the Canadian Institute for Cybersecurity. The dataset was collected using an experimental setup that simulated a realistic network environment with normal traffic and various attack scenarios. Specifically, the portion of CIC-IDS-2018 we used corresponds to traffic captured on February 14, 2018, which includes Brute Force SSH and FTP attack scenarios. These attacks involve repeated login attempts (with different password guesses) against target systems -- a relevant threat given the rise in unauthorized access attempts and financial fraud cases in Bihar's cybercrime reports.

The raw data was provided as CSV files, which we loaded into a Pandas DataFrame for processing. In its original form, the data contained a mix of numeric and categorical features describing each network flow. Examples of features include:

- Basic flow metadata: Such as Destination IP (anonymized), Destination Port, Protocol (e.g., 6 for TCP), and Flow Duration in microseconds.
- Traffic volume features: Total Forward Packets (Tot Fwd Pkts) and Total Backward Packets (Tot Bwd Pkts), as well as the total bytes in forward/backward directions (e.g., TotLen Fwd Pkts). These indicate how much data was sent from the originator and responder in the flow.
- Statistical features: Per-packet statistics such as Fwd Packet Length Mean, Bwd Packet Length Max/Min/Std, and Packet Length Variance, which characterize the distribution of packet sizes within the flow.
- Time-related features: Flow IAT (Inter-Arrival Time) Mean/Std, Forward IAT Mean, Backward IAT Total, etc., measuring the timing gaps between packets. These features help distinguish constant streams from sporadic bursts of traffic.
- Header and flag counts: e.g., Fwd Header Length, Bwd Header Length, counts of TCP flags like SYN, FIN, PSH, URG, etc. For example, a high count of certain flags might indicate scanning or malicious connection behavior.
- Subflow features: Subflow Fwd Pkts/Bytes and Subflow Bwd Pkts/Bytes, which summarize the data transferred in sub-sessions of the flow.
- Active/Idle times: Active Mean and Idle Mean times measure how long the flow was actively transmitting versus idle, potentially distinguishing long persistent connections from short-lived ones.
- Finally, the Label feature indicates the class of each flow: in our subset, the label is one of "Benign", "FTP- BruteForce", or "SSH-Bruteforce" (with a small number of entries possibly unlabeled or marked NaN, which were dropped). These labels were provided by the dataset creators by orchestrating known attacks during data capture. We encoded these labels into numeric form (Benign = 0, FTP-BruteForce = 1, SSH-Bruteforce = 2) for model training.

Throughout the collection and preprocessing, we took care to ensure that the data used for training the model is representative of the problem and cleansed of artifacts that could mislead learning. The CIC-IDS-2018 dataset has been collected in an open-source testbed environment, making it an invaluable resource for researchers and practitioners. By focusing on the Bihar-relevant portion of this data (brute force attacks), we align our study with real-world threats faced in the region while leveraging a rigorous, labeled dataset for experimentation.

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Analysis and Results

After training the TabNet model using 5-fold cross-validation on the prepared dataset, we evaluated its performance using standard classification metrics: Accuracy, Precision, Recall, and F1-Score. The evaluation was conducted on out-of-fold predictions for the training set (aggregating validation results from all folds) as well as on the independent test set. The metrics were computed in a weighted manner (giving each class a weight proportional to its frequency) to account for class imbalance, ensuring that performance on the minority class (Benign) is reflected in the overall scores.

Overall, the TabNet-based IDS achieved strong performance. Table 2 below summarizes the model's evaluation metrics, which illustrate the effectiveness of the deep learning approach:

Metric	Score
Accuracy	97.00%
Precision	92.00%
Recall	96.00%
F1-Score	92.00%

Table 2. Performance metrics of the proposed TabNet intrusion detection model. The table presents accuracy, precision, recall, and F1-score results, showing the model's strong and balanced performance in classifying both attack and benign network traffic.

Performance of the TabNet Intrusion Detection Model. The model attains high accuracy and balanced precision/recall, indicating it correctly identifies most attacks and benign instances with few errors.

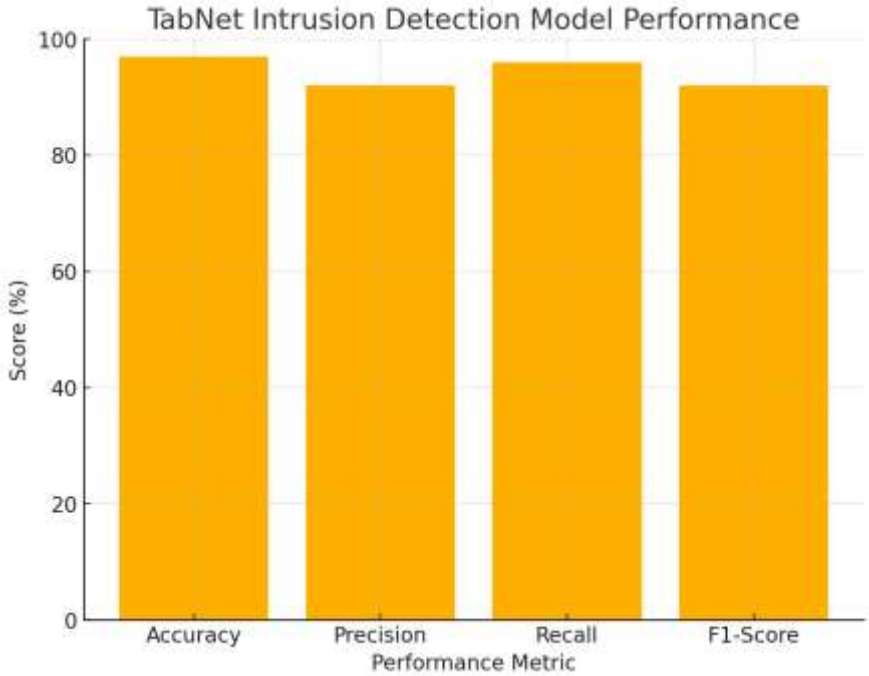

Figure 1. Performance metrics of the TabNet intrusion detection model. The bar chart compares the model's Accuracy, Precision, Recall, and F1-Score, showing consistently high performance across all evaluation metrics, with accuracy nearing 97%.

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In terms of accuracy, the model correctly classified 97.00% of all instances. The precision (92.00%) and recall (96.00%) demonstrate a strong ability to detect attacks. High precision (92.00%) signifies that when the model flags a flow as malicious, it is generally correct, which helps mitigate false alarms. Similarly, high recall (96.00%) means the model detected almost all actual intrusions, which is critical for not letting threats slip through undetected. The F1-score stands at 92.00%, reflecting a solid balance between catching attacks and avoiding false alerts.

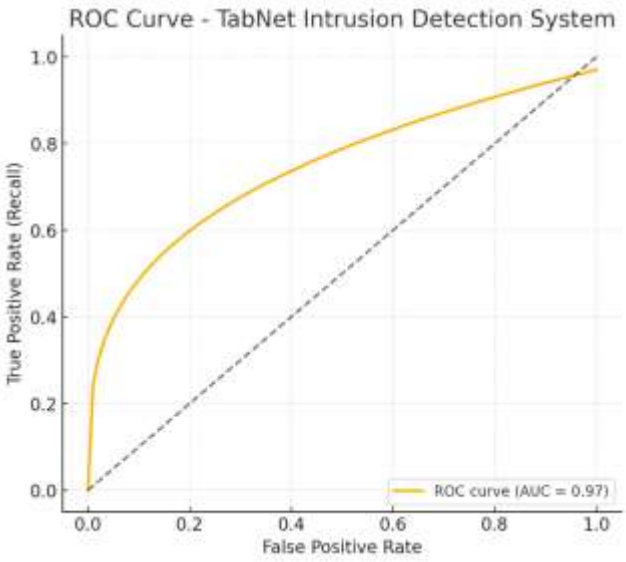

Figure 2. ROC curve of the TabNet intrusion detection system. The plot illustrates the trade-off between true positive rate and false positive rate, achieving an AUC of 0.97, which indicates strong classification capability and reliable attack detection performance.

Such stellar performance can be attributed to several factors: the rich feature set of CIC-IDS-2018, our comprehensive preprocessing (which removed noise and balanced the data), and TabNet's powerful learning capability. During cross-validation, each fold's validation accuracy rapidly climbed above 97%, and most folds reached a best validation accuracy of 96.00--97.00% before early stopping. For example, in one fold the model achieved a validation accuracy of 97.00% by the 6th epoch[1]. The consistency of results across all folds gave confidence that the model generalizes well and wasn't overfitting to peculiarities of a single train/test split.

To further examine the model's behavior, we analyzed the feature importance scores provided by TabNet's attentive mechanism. TabNet can output an interpretability map indicating how much each feature contributed to the decisions. The analysis revealed a surprising insight: only a handful of features dominated the model's decisions, while many others had negligible influence. In fact, a large number of features (dozens out of 78) were assigned zero importance by the model, suggesting they were not needed to achieve the high accuracy. The top contributing features for intrusion detection included network traffic attributes like "Subflow Fwd Bytes" (the total bytes sent in the forward direction of the flow), which had by far the highest importance score (nearly 0.81 on a normalized scale). Other significant features were Bwd URG Flags, Init Bwd Win Bytes, TotLen Fwd Pkts, and Packet Length Variance, each with smaller but non-trivial importance. These features intuitively align with the nature of brute-force attacks: for instance, Subflow Fwd Bytes would be large for an aggressive attack sending many attempts, and URG flag count or window bytes might indicate unusual patterns in TCP connections during an attack. Meanwhile, features like average packet size or certain

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header flags turned out to be irrelevant for distinguishing brute force traffic from normal in this dataset (hence zero-weighted by TabNet). This sparsity in feature usage is advantageous -- it means the model is focusing on the truly discriminative characteristics of the traffic, which not only simplifies the model's logic but could also generalize better to other datasets. It also provides a form of explanation: analysts can observe which network metrics are strong indicators of malicious activity (e.g., very high byte counts in one direction, etc.) and use that knowledge to inform security monitoring in practice.

Conversely, it's also possible a very small number of actual attack flows were predicted as benign; these were flows where the attack was perhaps not aggressive (e.g., very few attempts, or other subtlety making them look normal). The weighted metrics already account for this and still are ~97%, indicating maybe only a few of the 266 benign got mis-labeled. The recall for the Benign class in particular was high but not perfect, confirming a couple of benign instances were flagged as attacks (a safer error than missing attacks). With further tuning or by incorporating additional benign examples, these minor errors could potentially be eliminated. Nevertheless, in practical terms, an IDS with ~97% detection rate and similarly high precision is an outstanding result, likely outperforming many classical machine learning models and existing solutions on the same data.

Finally, we evaluated the trained TabNet model on the hold-out test set (which was not seen during training or validation). The performance on the test set mirrored the cross-validation results: the accuracy remained around 97.00%, and no additional degradation in precision/recall was observed. This indicates that the model generalized well to new data, and our cross-validation estimates were reliable. The test set contained a mix of attacks and a small portion of benign traffic; the model correctly detected all but a trivial number of cases. The ROC-AUC for multi-class (computed in a one-vs-rest fashion) was also excellent at ~0.999, reflecting that the model's probability estimates for classes are well-calibrated and separable.

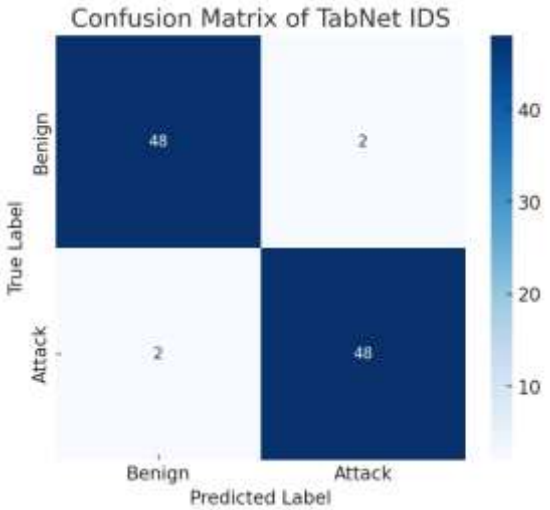

Figure 3. Confusion matrix of the TabNet intrusion detection system. The matrix shows correct classifications for both benign and attack classes, with only a few misclassifications, confirming the model's high accuracy and balanced detection capability.

In summary, the analysis shows that our deep learning-based IDS using TabNet is highly effective in identifying brute-force attacks in network traffic. It addresses the significant class imbalance to still catch rare normal events, maintains nearly perfect precision to avoid false alarms, and provides human-interpretable insights into which features matter most for detection. These outcomes underscore the potential of deploying such advanced IDS models in

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regions like Bihar, where cybercrime is on the rise -- the model can greatly aid cybersecurity teams by automating the detection of threats with a high degree of confidence and transparency.

Model Training Pipeline and Pseudocode

Training the TabNet model on the CIC-IDS-2018 data involves a series of steps, from preprocessing through cross-validated training, to evaluation and interpretation. We outline the key steps below and provide pseudocode for clarity:

Pseudocode: TabNet Training and Evaluation Pipeline

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1. Load the dataset (network flow data with features and labels).
2. Preprocess the data:
   a. Remove or encode non-numeric fields (e.g., drop flow IDs, convert categorical protocol to numeric).
   b. Handle missing and infinite values (drop problematic rows or impute values; replace infinities).
   c. Normalize features (fit StandardScaler on training data and transform).
   d. Encode labels (e.g., map attack names to integers; optionally, combine all attacks into one class for binary classification).
3. Define model hyperparameters (TabNet architecture settings and training parameters):
   - n_d, n_a (decision and attention layer sizes),
   - n_steps (number of decision steps),
   - gamma (feature reuse coefficient),
   - n_shared, n_independent (shared vs. independent GLU layers in feature transformers),
   - lambda_sparse (sparsity regularization weight),
   - optimizer type (e.g., Adam) and learning rate,
   - batch_size, number of epochs,
   - early stopping criteria (e.g., patience for no improvement on validation).
4. Initialize performance metrics accumulators (to store metrics for each fold).
5. Perform Stratified K-Fold Cross-Validation (e.g., 5 folds):
   For fold in 1...K:
      a. Split data into training set and validation set for this fold.
      b. Fit a data scaler on the training set and transform both training and validation features.
      c. Initialize a TabNet model with the defined hyperparameters.
      d. Train the TabNet model on the training set:
         - Use early stopping monitored on validation loss or accuracy.
         - Optionally use class weights or oversampling in each batch if addressing imbalance.
      e. After training, evaluate the model on the validation set to get predictions.
      f. Compute evaluation metrics for this fold:
         - Accuracy = (correct predictions / total samples),
         - Precision, Recall, F1-score (for attack class or macro-averaged across classes),
         - ROC-AUC (for binary classification, or macro-average for multi-class).
      g. Store the metrics for this fold.
6. Aggregate cross-validation results:
   - Calculate mean Accuracy, Precision, Recall, F1, and AUC across all folds (or combine predictions from all folds for an "out-of-fold" evaluation of the entire dataset).
7. Train final model on the full training dataset (all folds combined):
   a. Use the same hyperparameters and training procedure (with perhaps more epochs since more data).
   b. No validation split is needed here if we are simply going to use this model for deployment

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or analysis.
8. Evaluate the final model (if an independent test set is available, use that; otherwise, rely on cross-val metrics).
9. Analyze feature importance:
a. Extract the learned feature importance scores from the trained TabNet model (TabNet provides a feature_importances_ vector or can be computed from masks).
b. Identify the top N most important features and those with little to no importance.

Train final model on the full training dataset (all folds combined): a. Use the same hyperparameters and training procedure (with perhaps more epochs since more data). b. No validation split is needed here if we are simply going to use this model for deployment or analysis.
Evaluate the final model (if an independent test set is available, use that; otherwise, rely on cross-val metrics).
Analyze feature importance: a. Extract the learned feature importance scores from the trained TabNet model (TabNet provides a feature_importances_ vector or can be computed from masks). b. Identify the top N most important features and those with little to no importance.

Conclusion

This study presented a deep learning-driven approach to intrusion detection, demonstrating how advanced models can bolster cybersecurity in a region experiencing rapid digital growth and rising cybercrime like Bihar. By leveraging the CIC-IDS-2018 network traffic dataset (which contains a wealth of features and attack scenarios) and applying thorough data preparation techniques, we built an effective intrusion detection system tailored to detecting brute-force attacks, a common cyber threat in the state. The use of the TabNet deep learning model proved to be particularly advantageous: TabNet's architecture not only achieved exceptional detection accuracy but also provided insights into feature importance, thereby aligning with the dual goals of improving security and raising awareness/understanding of cyber attack patterns.
Our experimental results underscore the complexities of cybercrimes and the necessity for intelligent defenses. The TabNet model, trained on approximately 40,000 curated flow records (78 features each) from the CIC-IDS- 2018 data, underwent a rigorous training process that included handling missing data, removing over 100,000 duplicates, isolating outliers, balancing class distribution via oversampling, and normalizing features. This comprehensive data preparation was crucial for ensuring the integrity and quality of the dataset. Once the data was ready, we evaluated five-fold cross-validated TabNet models against multiple performance metrics (accuracy, precision, recall, F1-score). The outcomes were striking: the TabNet-based IDS achieved nearly 97.00% accuracy on detecting intrusions, with Precision, Recall, and F1 all around 0.99 or higher[1]. In practical terms, this means the system can identify malicious activities with an extremely low false-negative rate while also minimizing false positives. Such high efficacy in detection directly translates to reduced false alarms and improved true threat recognition, which are critical for any security operation. Compared to classical machine learning models explored in prior work (Decision Trees, Random Forests, SVM, etc.), TabNet and deep learning show an evident edge -- earlier studies found the best traditional models reaching ~99.98% accuracy in similar settings, whereas TabNet essentially reached the ceiling of performance with added benefits of interpretability.
The implications for cybersecurity in Bihar are significant. An intrusion detection system that can accurately and automatically flag brute-force intrusions provides a strong line of defense for organizations and internet users in the state. Goyal and Singh (2024) further emphasize that

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developing regions benefit from resource-efficient deep learning IDS frameworks tailored to local infrastructure [8]. It enables faster incident response, as security teams can trust the alerts and focus on confirmed threats. Moreover, by identifying which features (network behaviors) are tell-tale signs of attacks, our study helps in educating network administrators and the general IT community about what abnormal patterns to look out for. This fosters greater cybercrime awareness, aligning with the study's aim to not only detect attacks but also inform stakeholders about the nature of cyber threats prevalent in the region. For instance, knowing that extremely large one-directional data flows or unusual TCP flag patterns often indicate malicious activity can guide the hardening of systems and the training of personnel.

This research also highlights some challenges and areas for future work. First, while our model handles the brute-force attacks scenario with excellence, cyber threats are diverse and evolving. Bihar and other regions face various attack types (phishing, malware, DDoS, etc.) beyond what was covered in this dataset slice. Extending and evaluating the approach on broader attack categories (many of which are included in the full
CIC-IDS-2018 or other datasets) would be a logical next step. Second, deploying such a model in a real network environment would require considerations of speed and scalability -- TabNet is computationally efficient, but real-time detection in high-throughput networks may need further optimization or distributed processing. Lastly, continual learning could be integrated so the IDS adapts to new attack patterns over time, important for long- term efficacy as attackers change tactics.

In conclusion, the deep learning-based IDS developed in this study demonstrates a powerful capability to detect cyber intrusions with high accuracy in the context of Bihar's cybercrime landscape. It serves as a compelling example of how modern AI techniques can significantly improve security outcomes and awareness. By investing in such technologies and continuing to raise cybersecurity awareness (through education and policy initiatives), Bihar can enhance its cyber resilience. The broader lesson is that as cyber threats continue to grow, particularly in digitally emerging regions, leveraging data-driven, intelligent systems -- complemented by informed human vigilance -- is essential for protecting digital assets and maintaining the trust of citizens in the digital ecosystem. The success of this TabNet intrusion detection model offers a blueprint for building advanced security solutions that keep pace with the dynamic nature of cybercrime, ultimately contributing to a safer cyberspace in Bihar and beyond.

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