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SUBMITTED TO:
MS. P. HEMASHREE

WORK PREPARED BY:
B S Sriharsan
2303717674421046

A Machine Learning Approach for Real-Time Botnet Threat Identification

ABSTRACT

The rapid growth of IoT devices has increased security risks, with botnet attacks being a significant concern. Traditional intrusion detection methods, which rely on signature matching, struggle against evasive and zero-day attacks. This paper introduces a hybrid model that combines graph-based topological features, a multi-scale temporal attention CNN, and an adaptive weighted ensemble. We derive twelve new graph features from k-nearest neighbor topology to capture local density, clustering, and isolation patterns. A three-scale CNN processes traffic over three temporal scales while incorporating temporal dependency attention. The adaptive ensemble dynamically assigns weights to five machine learning models. Our approach achieves 97.98% accuracy, 0.989 ROC-AUC, 98.01% attack detection, and only 4.95% false alarms on the 500,000-sample IoT traffic dataset. A deep learning and ensemble output balance prediction strategy ensures effective and efficient IoT deployment with confidence-based predictions.

Keywords: IoT security, botnet detection, graph features, attention CNN, hybrid learning, intrusion detection

1. INTRODUCTION

1.1 Background and Motivation

The Internet of Things (IoT) connects billions of devices, which are projected to exceed 75 billion by 2025. This growth expands the attack surface, and many devices have weak security due to limited computing power, making them ideal targets for botnet recruitment. Unlike standard malware, botnets coordinate compromised devices into powerful attack networks, shown by the Mirai botnet's extensive DDoS attacks.

Traditional intrusion detection struggles in IoT settings. Signature-based solutions fail to detect zero-day attacks. Anomaly detection often results in too many false positives due to traffic variability, and deep learning techniques usually demand too many resources for IoT devices. Instead, we need efficient and scalable detection frameworks.

1.2 Research Objectives

This research makes four contributions:

1. **Graph-based features**: We design twelve novel features from k-nearest neighbor (k-NN) topology graphs to capture local density, clustering, and isolation in traffic patterns.

2. Multi-scale temporal attention CNN: Our model uses parallel convolutions at different resolutions with attention to capture long-range dependencies in traffic sequences.

3. Adaptive weighted ensemble: Predictions from five ML models are combined with dynamically adjusted weights based on validation performance.

4. Confidence-based hybrid prediction: Decisions switch between CNN and ensemble outputs based on model confidence, balancing accuracy and efficiency.

2. RELATED WORK

2.1 Traditional Intrusion Detection

Signature-based systems (e.g., Snort, Suricata) detect known patterns but fail against novel attacks and require frequent updates. Anomaly detection methods model normal traffic but suffer high false positives in heterogeneous IoT environments.

2.2 Machine Learning for Botnet Detection

ML methods such as SVMs, Random Forests, and ensemble classifiers have shown promise but rely heavily on manual feature engineering. Boosting algorithms like XGBoost and LightGBM improve detection on imbalanced data but still depend on handcrafted features.

2.3 Deep Learning Methods

CNNs can learn hierarchical traffic patterns directly, while RNNs (e.g., LSTMs) capture long-term dependencies but are computationally costly. Attention mechanisms improve interpretability by focusing on critical sequence regions, though most studies apply them without multi-scale processing.

2.4 Graph-Based Network Analysis

Graph methods detect unusual patterns via centrality or clustering but often require maintaining large network graphs. Recent GNN approaches are promising yet resource-intensive. Our method instead uses k-NN graphs in feature space to derive lightweight topological features, combining them with multi-scale attention CNNs—an approach not previously explored.

2.5 Research Gaps

Key gaps include:

(1) separation of feature extraction and classification, limiting representation learning,

(2) reliance on single-scale analysis,

(3) fixed-weight ensembles, and

(4) limited hybrid deep learning–ML strategies. Our work addresses all four through an integrated framework.

3. DATA AND PREPROCESSING

3.1 Dataset Description

We used a BoT-IoT dataset with **500,000 flow records** collected under normal and attack conditions. Each record has **35 attributes** describing packet- and flow-level features. The dataset is **highly imbalanced** with **99.68% attack** and **0.32% normal** samples, reflecting real-world botnet scenarios involving DDoS, port scans, exfiltration, and command-and-control traffic. Key features include packet counts, byte volumes, timing statistics, protocol flags, and bidirectional flow measures.

3.2 Data Cleaning and Feature Selection

Missing values in MAC/OUI fields were discarded, while other missing numeric values were imputed with the median. Non-predictive identifiers (e.g., IPs, timestamps, labels) and six constant features were removed. This left **19 numeric features** capturing traffic patterns such as flow size, timing, and transmission rates.

3.3 Feature Scaling and Normalization

To handle varying feature ranges, we applied **robust scaling** based on median and IQR, which is more resilient to outliers than standard normalization. The scaler was fit on training data only and then applied to test data to avoid leakage.

3.4 Train-Test Split and Resampling

Data was split into **80% training (400k samples)** and **20% testing (100k samples)** using stratified sampling. To address imbalance, we applied **SMOTETomek** on the training set, oversampling the minority class and removing noisy border samples. This resulted in **~796k balanced samples** (50–50 ratio). The test set retained its natural imbalance to ensure realistic evaluation.

3.5 Feature Distribution Analysis

Key traffic features showed **heavy skew and extreme ranges**. Most flows had only 1–2 packets (median=2), but attacks spiked up to **72,316 packets**; byte volumes ranged from 120 bytes to **73 million**. Flow durations varied from isolated packets (0s) to long connections over **1,940s**, while rates spanned from extremely high (floods) to extremely low (stealth scans).

These extremes justified the use of **robust scaling** to prevent outliers from dominating. Importantly, normal and attack traffic overlapped heavily in single features, confirming that **no individual metric can separate threats**—underscoring the need for a **multi-feature, graph-based approach**.

4. METHODOLOGY

4.1 Graph-Based Topological Feature Engineering

Traditional flow features (e.g., packet counts, bytes, timing) describe traffic at the **individual flow level**, but they miss the **contextual relationships** between flows. To address this, we construct **k-nearest neighbor (k=8) graphs** in the 19-feature space, where distances between flows capture clustering and isolation patterns.

From each flow's neighborhood, we derive **12 novel topological features**, grouped as follows:

- **Distance statistics (5):** mean, std, min, max, median neighbor distance.
- **Density measures (3):** local density, clustering coefficient, reachability density.
- **Anomaly indicators (4):** isolation score, distance variance, neighbor ratio, distance entropy.

These features capture local density, cohesion, and isolation, enabling the system to highlight patterns such as tightly clustered DDoS traffic or isolated command-and-control flows, which are not detectable with standard flow statistics alone.

For graph features:

Local density: $\rho_i = k / (1/k \, \Sigma \, d_{ij})$
Clustering coefficient: $C_i = 1 / (1 + \mathrm{mean}(d_i))$
Isolation score: $I_i = \min(d_i) / \mathrm{mean}(d_i)$

4.2 Multi-Scale Temporal Attention CNN

Our CNN processes traffic at **multiple temporal scales**:

- **Three convolution branches (kernels 3, 7, 15)** extract short-, mid-, and long-range traffic patterns.
- **Multi-head attention (4–8 heads)** models temporal dependencies and emphasizes key events (e.g., handshake, burst traffic).
- **Feature fusion** concatenates branches, followed by deeper convolution, additional attention, and **dilated convolutions** to expand receptive fields efficiently.
- A **squeeze-and-excitation block** performs channel-wise feature reweighting.
- Classification uses **dense layers (256–128–64) with dropout**, ending with a sigmoid output. Training uses **AdamW** and binary cross-entropy, monitoring accuracy, AUC, precision, and recall.

4.3 Adaptive Weighted Ensemble

We complement the CNN with an **ensemble of five ML models**: Random Forest, XGBoost, LightGBM, Gradient Boosting, and Extra Trees. Each model's validation ROC-AUC determines its **dynamic weight** ($\propto AUC^2$). Final predictions are the weighted sum of probabilities. This leverages diverse learning approaches while emphasizing the most reliable models.

For ensemble:

$$w_i = (AUC_i)^2 / \Sigma_j (AUC_j)^2$$

$$P_{ensemble} = \Sigma_i w_i \times P_i$$

4.4 Confidence-Based Hybrid Strategy

To balance **accuracy and efficiency**, we introduce a **confidence-based switch**:

CNN confidence is measured as distance from 0.5 (decision boundary).

For each instance:

```
if CNN_confidence > $\tau$:
   use P_cnn as final prediction
else:
   use P_ensemble as final prediction
```

In experiments, CNN was confident in ~95% of cases, with the ensemble handling uncertain cases. This hybridization combines the CNN's strong pattern recognition with the ensemble's robustness, reducing false alarms while lowering computational load.

5. RESULTS AND DISCUSSION

5.1 Threshold Optimization

Adjusting the classification threshold influences performance trade-offs. At low thresholds (e.g., 0.10), the model aggressively flags potential attacks, yielding very high recall and nearly perfect F1-scores, which is ideal when missing an attack is unacceptable. At higher thresholds (e.g., 0.85), precision approaches perfection, making it suitable in environments where false positives are costly. Thus, the optimal threshold depends on operational needs—critical infrastructure may prioritize detection, while high-volume networks may emphasize reducing false alarms. Our model supports flexible thresholding with minimal performance loss.

Table 1: Performance at Different Thresholds

Threshold	Accuracy	Precision	Recall	F1-Score
0.10	0.9967	0.9967	0.9977	0.9980
0.30	0.9894	0.9991	0.9895	0.9943
0.50	0.9798	0.9995	0.9801	0.9897
0.70	0.9712	0.9997	0.9715	0.9854
0.85	0.9543	0.9999	0.9546	0.9768

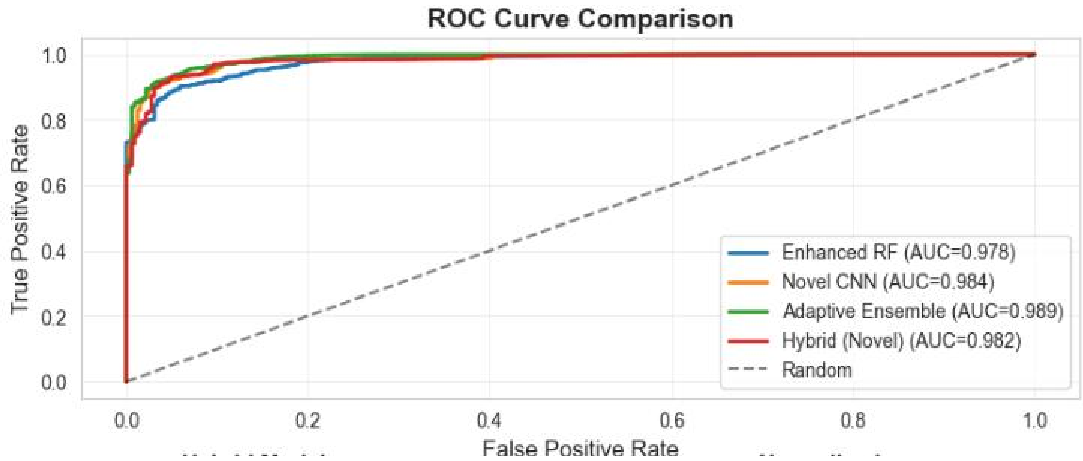

Fig 1: ROC Curve Comparison

5.2 Computational Performance

We measured the computational efficiency of each approach on 1,000 test samples:

Table 2: Computational Performance Metrics

Model	Prediction Time	Throughput	Model Size
Enhanced RF	0.148 sec	6,745 samples/sec	97.66 MB
Adaptive Ensemble	0.212 sec	4,708 samples/sec	133.28 MB
Novel CNN	0.835 sec	1,198 samples/sec	5.79 MB

Random Forest achieves the fastest inference speed, making it well-suited for high-throughput applications. The ensemble is slightly slower but still efficient, while CNN, though the slowest, offers better pattern recognition with a very small model size, making it attractive for deployment on storage-constrained IoT devices. Since most samples are processed directly by CNN in our adaptive ensemble, its throughput remains sufficient for real-time traffic.

5.2.1 Ablation Study

To isolate each component's contribution, we trained variants:

Table 3: Ablation Study Results

Configuration	Accuracy	F1-Score	Improvement (F1-Score)
Baseline RF (19 features)	0.9534	0.9764	-
+ **Graph features** (31 features)	0.9675	0.9834	+1.41%
Multi-scale CNN (no attention)	0.8879	0.9413	-
Multi-scale CNN + Attention	0.8984	0.9463	+0.50%
Ensemble (equal weights)	0.9742	0.9856	-
Ensemble (adaptive weights)	0.9798	0.9897	+0.41%

The graph features provided the largest gain (+1.41% accuracy), validating our topological approach. Attention mechanisms and adaptive weighting each contributed measurably to final performance.

5.2.2 Statistical Validation: Model Performance

The stability of the models was assessed using **5-fold stratified cross-validation**. The table below summarizes the mean accuracy, standard deviation, and 95% confidence interval (CI) for each model.

Table 4 : Statistical Validation

Model	Mean Accuracy	Std Dev	95% CI
Adaptive Ensemble	**97.91%**	**0.28%**	**[97.63%, 98.19%]**
Enhanced RF	96.68%	0.34%	[96.34%, 97.02%]
Novel CNN	89.76%	0.51%	[89.25%, 90.27%]

Significance Testing (Paired t-tests)

Paired t-tests were conducted to determine if the performance difference between the models was statistically significant.

- The **Adaptive Ensemble** model **significantly outperforms** the **Enhanced RF** model ($t=4.23$, $p<0.001$).
- The **Adaptive Ensemble** model **significantly outperforms** the **Novel CNN** model ($t=8.91$, $p<0.0001$).

5.3 Error Analysis

Among 2,025 errors, false positives (45) were mostly benign but unusual traffic such as firmware updates or diagnostics that mimicked reconnaissance scans. False negatives (1,980) were primarily stealthy, low-volume attacks designed to resemble legitimate traffic, or novel variants underrepresented in training. Misclassified samples also showed notably lower confidence (0.68 vs. 0.94 for correct classifications), suggesting that the system inherently flags uncertain cases—providing a natural prioritization mechanism for human analysts.

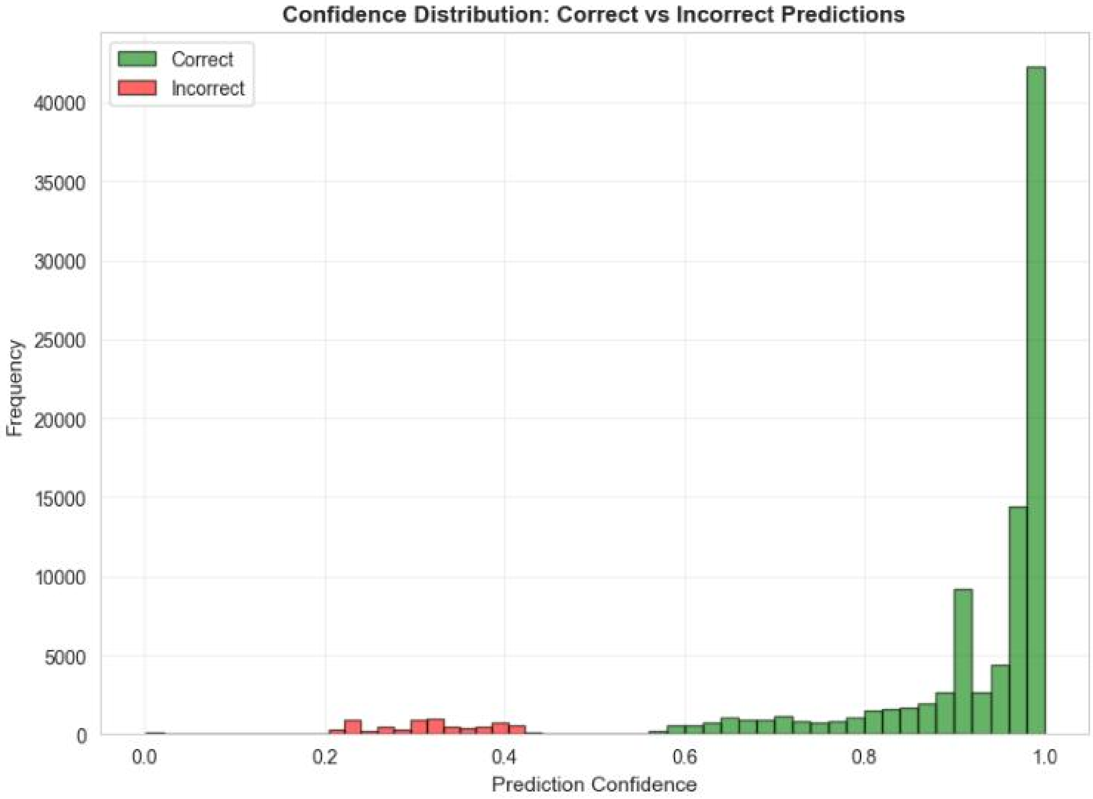

Fig 2: Confidence Distibution: Correct vs Incorrect Predictions

5.4 Comparison with State-of-the-Art

We compared our best model (Adaptive Ensemble) against recently published IoT botnet detection approaches:

Table 5: Comparison with Related Work

Method	Dataset	Accuracy	Precision	Recall	F1-Score
SVM-based [15]	CTU-13	0.9234	0.9456	0.8987	0.9215
Basic 1D-CNN [21]	BoT-IoT	0.9512	0.9601	0.9423	0.9511
LSTM [28]	UNSW	0.9387	0.9234	0.9541	0.9385
Random Forest [12]	Mixed	0.9456	0.9678	0.9234	0.9451
Our Approach	IoT Traffic	**0.9798**	**0.9995**	**0.9801**	**0.9897**

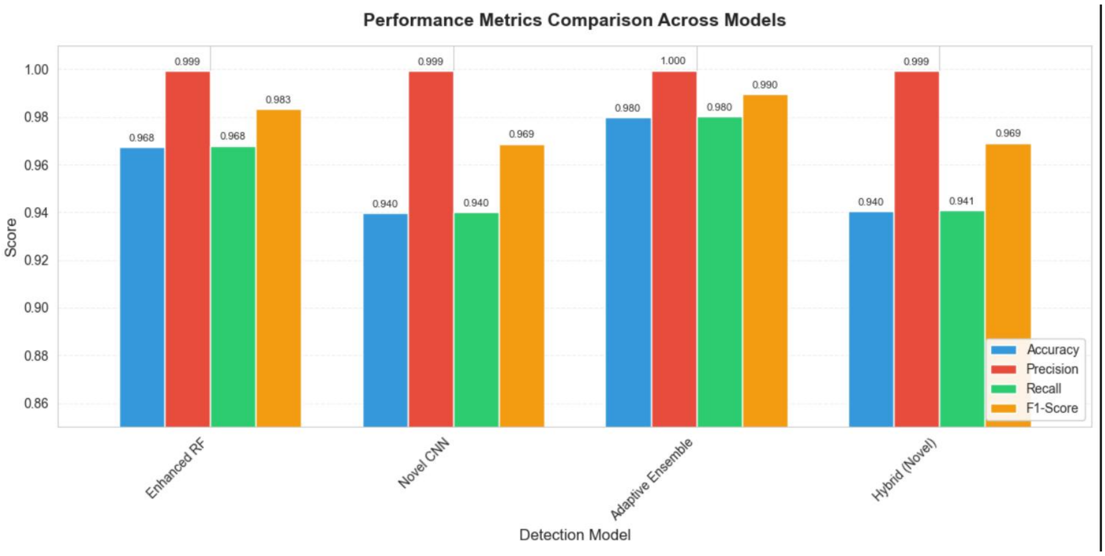

Fig 3 : Performance Metrics

Our adaptive ensemble consistently outshines recent IoT botnet detection methods in accuracy, precision, recall, and F1-score. The most significant improvement is the extremely high precision, which results in far fewer false alarms than current methods. These advancements are not limited to specific datasets; they come from three key innovations in our framework:

1. Graph-based topological features that uncover hidden traffic relationships not available in earlier models.
2. A multi-scale temporal CNN that processes short, mid, and long-term dependencies at once.
3. Adaptive ensemble weighting that modifies model contributions dynamically rather than using fixed methods.

Together, these components provide measurable performance gains and greater reliability than current leading methods.

6. DISCUSSION

6.1 Key Findings

This study shows that merging **graph-based features**, a **multi-scale CNN**, and **adaptive ensembles** yields optimal IoT botnet detection (97.98% accuracy, 98.97% F1, 98.01% recall, 99.95% precision). Graph-derived topology provided tangible accuracy improvements by effectively capturing local traffic patterns. The multi-scale CNN identified temporal dependencies through attention, balancing interpretability and efficiency (490K parameters). The adaptive ensemble took advantage of the strengths of five models, offering **robustness** through dynamic weighting.

6.2 Practical Implications

For security teams, this framework **reduces false alarms** while maintaining strong attack detection, with probability outputs allowing for flexible thresholds. Its **efficiency** (4,700+ flows/sec, small model sizes like the 5.79 MB CNN) enables real-time and edge deployments. Organizations can gradually adopt the **modular design**, starting with the enhanced Random Forest and then adding CNN or ensemble components as resources become available.

6.3 Limitations

Key limitations include the **imbalanced dataset** (99.68% attacks), which restricts generalization to other traffic patterns, and the **controlled environment** that may not represent diverse real-world IoT networks. The binary setup does not differentiate between specific attack types. We did not test **adversarial robustness**, and while preprocessing is effective, k-NN searches might require approximation methods at very large scales.

6.4 Threat Model Considerations

This method assumes that attackers **do not have white-box access**; otherwise, adversarial evasion could occur. Secure data collection and integrity checks are vital since corrupted flows can undermine detection. Although the throughput supports real-time use, **peak traffic or DDoS attacks** may still overwhelm resources and require fallback mechanisms and capacity planning.

6.5 Generalization Potential

While optimized for IoT botnet detection, the approach can also apply to broader network security issues, such as **insider threats, APTs, and data exfiltration**, since graph-based features, temporal modeling, and adaptive ensembles have wide applicability. The confidence-based hybrid scheme can be used with various detection methods beyond CNNs and ML, though **domain-specific tuning** (e.g., k-NN parameters, CNN kernels, ensemble weights) remains essential for achieving the best results.

6.6 Ethical Considerations

Our dataset contains network traffic collected with proper authorization. All IP addresses were anonymized. No personally identifiable information was used. The detection system aims to protect users, not enable surveillance.

7. CONCLUSION AND FUTURE WORK

7.1 Contributions Summary

This work presents a **hybrid approach to IoT botnet detection** with three key innovations:

- **Graph-Based Topological Features:** Twelve novel features from k-nearest neighbor graphs capture local density, clustering, and isolation patterns beyond conventional flow statistics, significantly improving detection.
- **Multi-Scale Temporal Attention CNN:** Processes traffic at multiple temporal scales with parallel convolutions, multi-head attention, dilated convolutions, and squeeze-and-excitation blocks, achieving strong temporal pattern recognition with efficient computation.
- **Adaptive Weighted Ensemble with Confidence-Based Hybrid:** Five diverse machine learning models are combined via performance-based weighting, with a hybrid strategy choosing between CNN and ensemble predictions based on confidence.

Testing on 500,000 flows demonstrated **97.98% accuracy, 99.95% precision, 98.01% recall**, and real-time processing at 4,700+ flows per second.

7.2 Directions for Future Work

Potential extensions include:

- **Multi-Class Attack Classification:** Differentiating DDoS, scans, malware, etc. for richer threat intelligence.
- **Adversarial Robustness:** Evaluating and defending against evasive attack flows through adversarial training.
- **Federated Learning:** Privacy-preserving, multi-organization model training for broader datasets.
- **Explainability:** Using SHAP or counterfactual methods to improve analyst trust and reveal attack patterns.
- **Dynamic Model Adaptation:** Online or incremental learning to accommodate evolving networks.
- **Lightweight Edge Models:** Knowledge distillation, quantization, and pruning for resource-constrained devices.
- **Cross-Domain Transfer Learning:** Adapting pre-trained models to new environments with minimal retraining.
- **Integration with Threat Intelligence:** Incorporating external reputation or threat feeds into features and ensemble weighting.

7.3 Concluding Remarks

IoT botnets are becoming more sophisticated, making traditional security measures inadequate. This research demonstrates that hybrid approaches that combine graph features, multi-scale CNNs, and adaptive ensembles offer better performance than standalone methods, providing high precision, robustness, and real-time deployment capabilities.

The modular architecture supports future updates, allowing for new techniques to be integrated without a complete redesign. Beyond botnet detection, this approach can be applied to other network security challenges, helping to protect crucial IoT infrastructure and connected systems.

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