

AI/ML FOR
NETWORKING

AI NETWORK TRAFFIC ANALYSIS

P R E S E N T A T I O N

TEAM:



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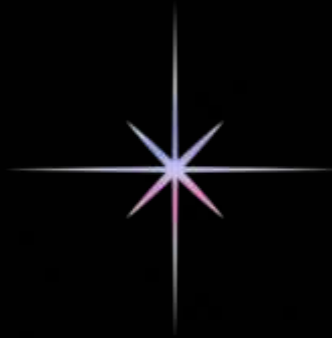
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Problem Summary:



Modern networks face increasing challenges in monitoring and securing traffic due to the exponential growth of data, encrypted communication, and sophisticated cyber threats. This presentation explores how AI and machine learning can revolutionize network security and operations.

Modern networks = Huge Data + Encryption + Advanced Threats → Old methods are not enough.

- Traditional rule-based security and DPI are failing.
- Manual classification is slow and error-prone.

→ Need AI-based real-time analysis to:

- Detect patterns.
- Spot anomalies.
- Secure encrypted traffic.





Deliverables:

1. Traffic Classification Model

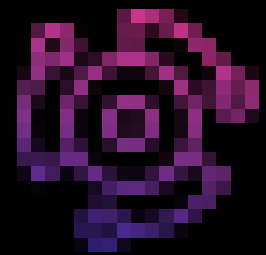
- AI model that identifies types of traffic (e.g., WhatsApp, YouTube, VPNs) from packet metadata or flow patterns.

2. Threat Detection & Anomaly Framework

AI system that detects:

- Malware.
- DDoS attacks.
- Suspicious behaviors.
- Unknown anomalies.





Model Information



ARCHITECTURE

Ensemble Model: Random Forest + XGBoost

FEATURES USED

32 features

DATA SPLIT

70% Train / 15% Validation / 15% Test

OBJECTIVE

Classify network traffic and detect threats/anomalies

ALGORITHM

Multi-class Classification

EVALUATION METRICS

Accuracy, Precision, Recall, F1 Score, Confusion Matrix

TOP FEATURES

Flow Duration | Total Bytes | Packet Inter-arrival Time (Mean) |
Flow Bytes per Second | TCP Flags



- data set is attached to the

id																								
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	
1	id	timestamp	sourceIP	destination	sourcePort	destinationPort	protocol	flowDuration	totalBytes	totalPackets	avgPacketSize	minPacketSize	maxPacketSize	flowsPerSecond	timeBetweenFlows	flowBytes	packetInterArrival	packetInterDeviation	tcpFlags	flowIdleTime	classification	confidence	anomalyScore	
2	b6c66587	2025-03-2 101.121.1	172.82.63	4347	23	FTP	78.34726	30876	149	207	143	268	3	199.1785	394091.6	0.525821	0.128148	0.128148	{"SYN":false;ACK:true;FIN:false}	666.957	DDoS	(
3	b6c7e116	2025-04-1 233.161.1	130.213.6	36373	21	UDP	64.06131	605	1	598	336	792	9	191.144	9444.078	64.06131	32.07151	32.07151	{"SYN":false;ACK:true;FIN:true}	163.8791	BENIGN	(
4	96b7d7fa	2025-04-1 145.163.2	231.6.169	60117	143	HTTP	188.8425	17059	65	260	206	390	1	469.9407	90334.56	2.905268	1.537309	1.537309	{"SYN":false;ACK:false;FIN:true}	448.7207	DoS	(
5	e93ed233	2025-04-0 40.62.202	204.235.1	51159	5432	FTP	193.9229	3670	12	283	160	418	8	198.8241	18925.05	16.16024	5.048327	5.048327	{"SYN":false;ACK:true;FIN:false}	382.1817	BENIGN	(
6	38348612	2025-04-1 87.248.22	117.9.102	63204	34940	ICMP	135.0677	18637	99	188	106	308	9	486.4082	137982.7	1.36432	0.808509	0.808509	{"SYN":false;ACK:true;FIN:false}	194.9856	DoS	(
7	464c5a6f	2025-04-0 197.214.1	252.136.1	57124	23	TCP	39.16879	2889	9	290	152	456	9	71.2799	73757.7	4.352088	0.593799	0.593799	{"SYN":false;ACK:true;FIN:false}	439.8821	BENIGN	(
8	b2d270dd	2025-04-1 60.220.16	128.38.25	12294	587	SMTP	227.8471	5569	20	273	187	358	1	421.5469	24441.83	11.39236	3.161837	3.161837	{"SYN":false;ACK:true;FIN:false}	925.2707	BENIGN	(
9	06c46d5c	2025-04-2 36.45.129	128.97.31	9592	443	SMTP	304.2942	6333	48	131	101	210	2	12.23135	20812.1	6.339462	2.614335	2.614335	{"SYN":false;ACK:true;FIN:true}	632.2549	BENIGN	(
10	6aa6ee3a	2025-04-1 98.208.11	51.180.22	54153	993	HTTPS	230.5852	3121	33	92	56	138	4	168.795	13535.13	6.987429	2.007601	2.007601	{"SYN":false;ACK:false;FIN:true}	728.5418	BruteForce	(
11	9c344f3a	2025-04-1 16.62.86.9	27.182.43	4502	25	SMTP	460.6482	9542	28	332	189	530	4	284.6617	20714.29	16.45172	7.286806	7.286806	{"SYN":true;ACK:true;FIN:false}	931.4798	BENIGN	(
12	58a51f3c	2025-04-2 196.150.1	85.157.10	65136	52992	ICMP	282.158	9281	24	385	236	644	2	300.013	32892.91	11.75658	3.64244	3.64244	{"SYN":false;ACK:false;FIN:false}	367.2998	BENIGN	(
13	3ba51eb8	2025-04-1 176.155.2	173.155.2	54103	110	FTP	255.6995	435	0	586	360	713	5	258.9813	1701.216	Infinity	Infinity	Infinity	{"SYN":false;ACK:false;FIN:false}	236.9513	BENIGN	(
14	ad25addf	2025-04-2 199.42.10	146.102.1	31188	995	FTP	16.50752	1747	12	142	89	237	1	383.6221	105830.6	1.375626	0.777241	0.777241	{"SYN":false;ACK:true;FIN:false}	135.8601	BENIGN	(
15	354eab3c	2025-04-2 79.1.201	189.4.207.2	7465	3306	HTTPS	483.139	4990	15	315	190	393	4	404.2567	10328.29	32.20927	12.70427	12.70427	{"SYN":true;ACK:true;FIN:false}	858.9733	BENIGN	(
16	c808df07	2025-04-0 115.140.2	37.109.12	45798	25	TCP	45.84105	35834	240	149	92	229	3	459.2494	781701.2	0.191004	0.076642	0.076642	{"SYN":false;ACK:true;FIN:false}	46.11867	DDoS	(
17	f3a2984a	2025-04-0 172.189.5	75.175.22	35423	443	TCP	276.7028	2260	8	277	170	380	2	97.80839	8167.609	34.58785	20.51363	20.51363	{"SYN":true;ACK:true;FIN:false}	142.1964	Botnet	(
18	ced5b5b0	2025-04-1 12.202.23	145.46.50	37360	23	ICMP	376.7235	9229	70	131	103	204	2	19.43236	24498.08	5.381764	2.254633	2.254633	{"SYN":false;ACK:true;FIN:false}	28.3561	BENIGN	(
19	2a4a9833	2025-04-1 187.104.1	58.113.38	59495	993	HTTP	691.9584	2310	16	141	75	181	10	231.8124	3338.351	43.2474	4.742527	4.742527	{"SYN":false;ACK:true;FIN:false}	337.4273	Botnet	(
20	c41572fd	2025-03-2 47.83.45	111.248.18	46990	53	HTTPS	748.6829	8805	41	213	147	318	9	174.4492	11760.65	18.26056	3.475182	3.475182	{"SYN":false;ACK:true;FIN:false}	439.2405	Malware	(
21	f39eaa9c	2025-04-2 135.118.2	223.140.1	5032	11592	FTP	285.7428	7440	37	198	123	300	10	166.6016	26037.4	7.722778	3.962142	3.962142	{"SYN":true;ACK:true;FIN:false}	659.5145	BENIGN	(
22	086f3194	2025-04-1 212.223.1	41.34.98.1	18715	3389	FTP	96.17191	43964	227	193	153	283	6	385.0382	457139.7	0.423665	0.229727	0.229727	{"SYN":true;ACK:true;FIN:false}	772.9223	DDoS	(
23	ffc5f1bb	2025-04-1 127.158.1	139.96.57	36179	1693	FTP	959.0337	962	7	123	78	183	2	502.9495	1003.093	137.0048	36.91946	36.91946	{"SYN":false;ACK:true;FIN:false}	588.4717	Botnet	(
24	57dce9ab	2025-04-0 84.187.13	98.139.21	22612	23	TCP	83.65447	5589	25	220	167	304	10	332.2287	66810.53	3.346179	1.114197	1.114197	{"SYN":false;ACK:true;FIN:false}	677.6342	BENIGN	(
25	e3d71caa	2025-04-1 186.14.13	9.76.55.23	7085	80	ICMP	81.79851	55054	350	157	108	227	9	188.2819	673044.1	0.23371	0.111494	0.111494	{"SYN":true;ACK:true;FIN:false}	400.8887	DDoS	(
26	11f6deb9	2025-04-0 102.207.1	189.87.24	47118	5432	UDP	51.80192	2368	5	428	306	645	3	32.13894	45712.59	10.36038	3.042554	3.042554	{"SYN":false;ACK:true;FIN:false}	787.7866	BENIGN	(
27	5e2816bd	2025-04-1 1.161.50	183.195.14	55550	50231	SMTP	21.82695	420	1	345	245	572	1	279.3268	19242.27	21.82695	10.07262	10.07262	{"SYN":false;ACK:true;FIN:false}	731.6422	BENIGN	(
28	f5d55607	2025-04-1 61.38.30	182.68.188	27476	21	SMTP	122.5528	2356	8	292	189	362	5	289.5117	19224.36	15.3191	5.221431	5.221431	{"SYN":false;ACK:true;FIN:false}	415.8557	Botnet	(
29	bc8b0be1	2025-04-0 239.80.36	174.155.1	56624	143	TCP	301.2486	15345	40	379	250	537	3	80.23158	50937.99	7.531215	3.238498	3.238498	{"SYN":false;ACK:false;FIN:false}	353.7998	DoS	(

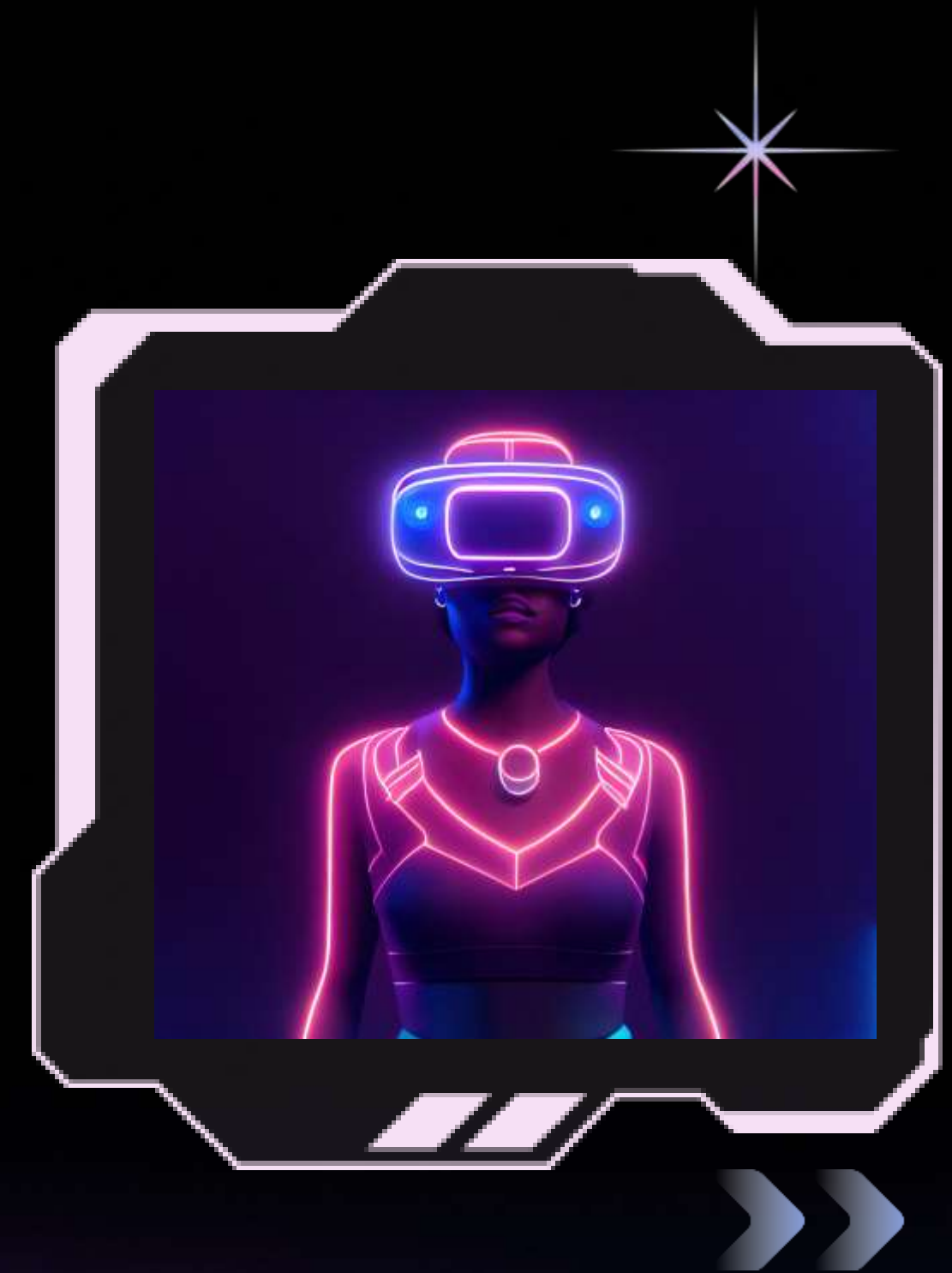


Traffic Classification Model

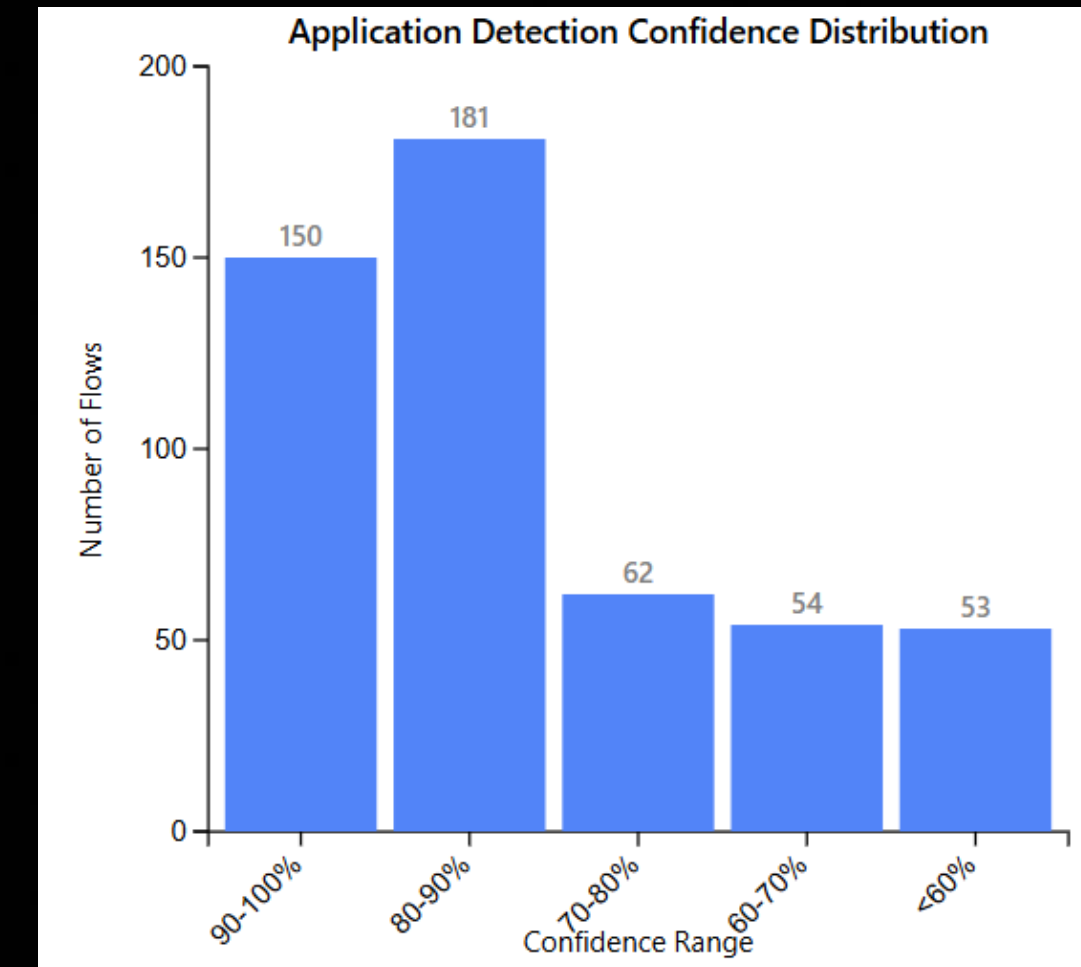
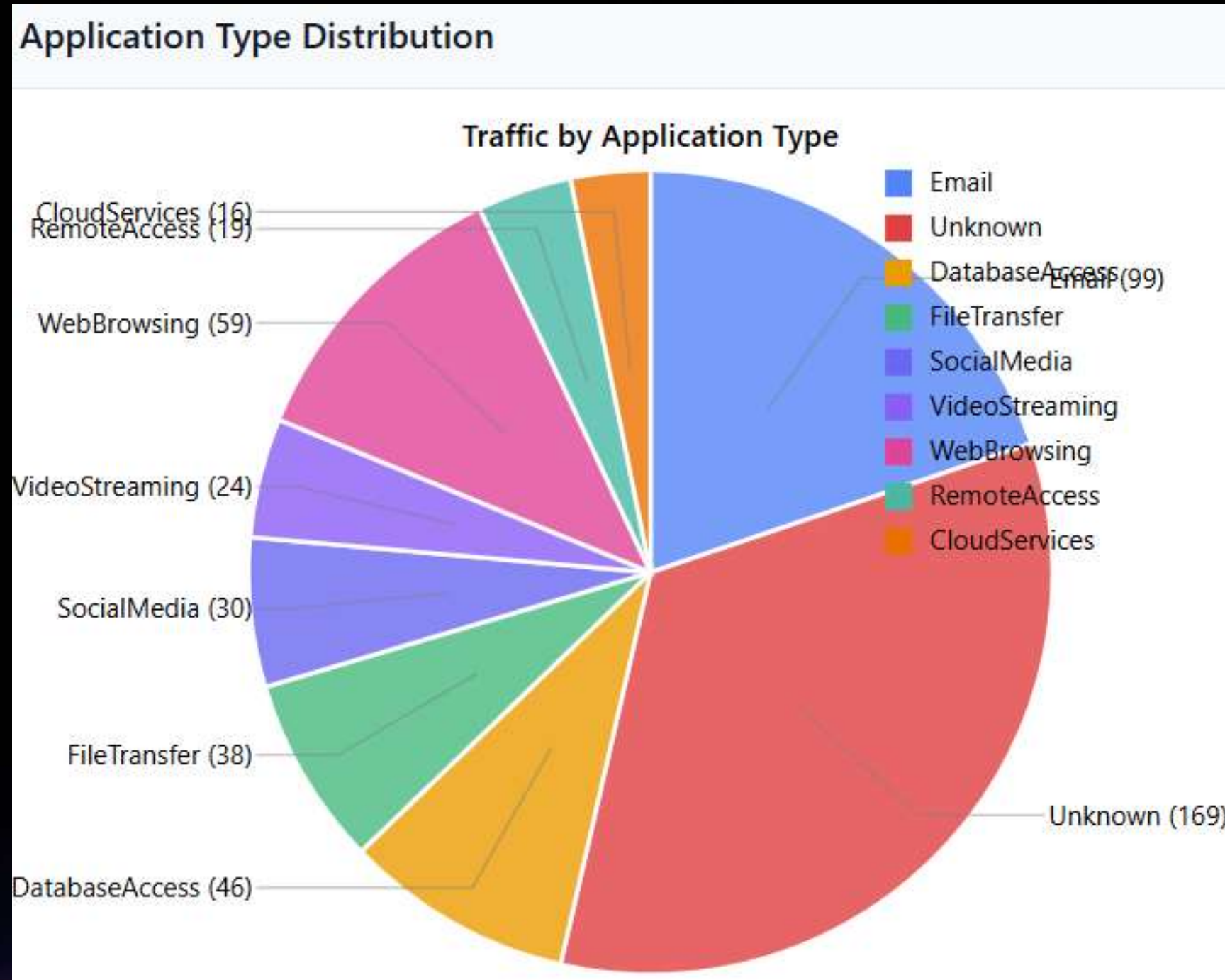
Detected applications include:

1. Email
2. Web Browsing
3. Social Media
4. File Transfer
5. Database Access
6. Video Streaming
7. Remote Access
8. Cloud Services
9. Unknown Applications

- Web browsing, email, and unknown traffic are among the most commonly observed application types.
- Remote access and cloud services were identified less frequently.



Classification of applications:



Application Detection Confidence:

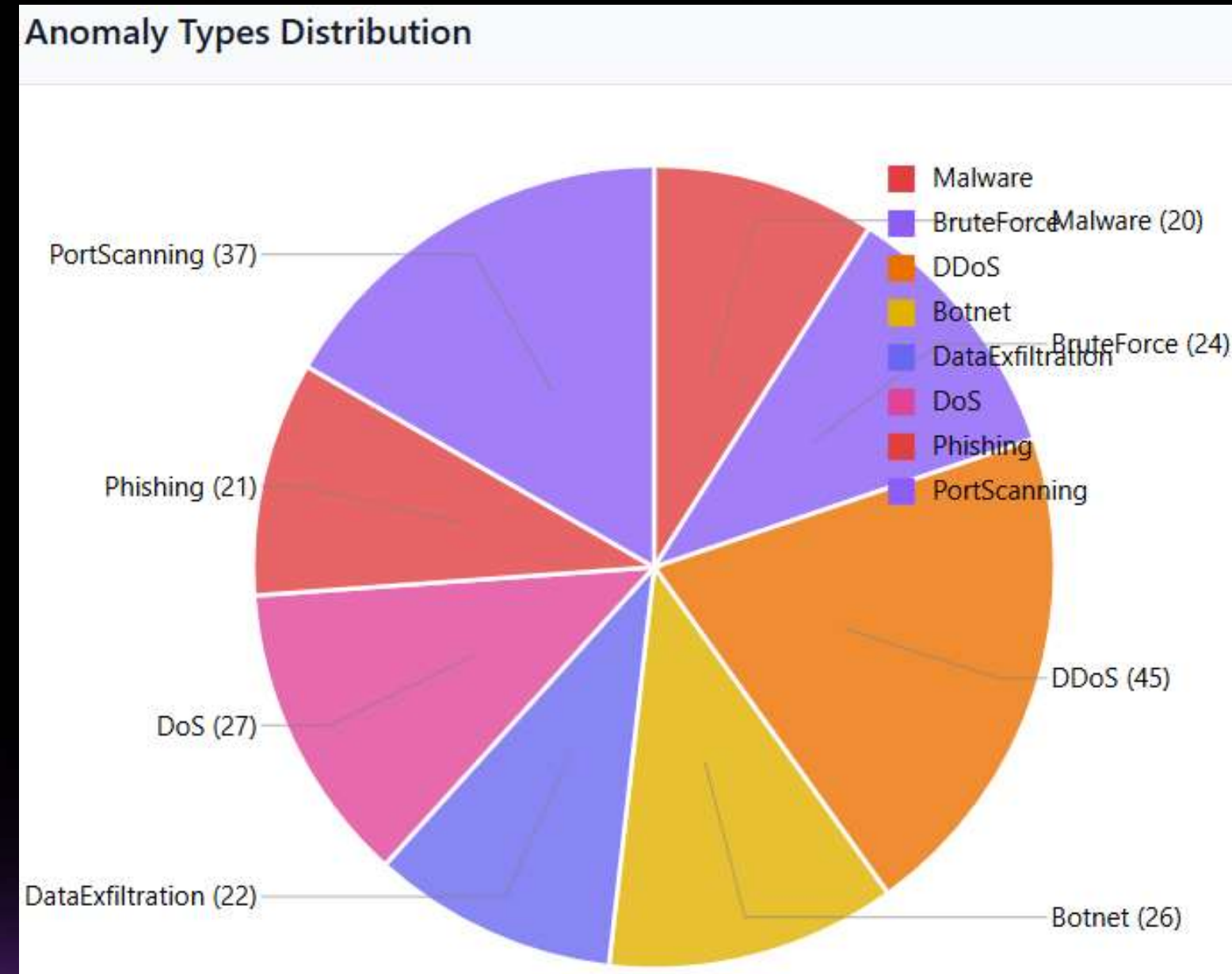
- Majority of application detections achieved high confidence levels (above 80%).
- A smaller proportion falls into lower confidence ranges (below 70%).
- Overall, application identification is considered reliable and robust.

Threat Detection & Anomaly Identification Framework

Detected anomaly categories include:

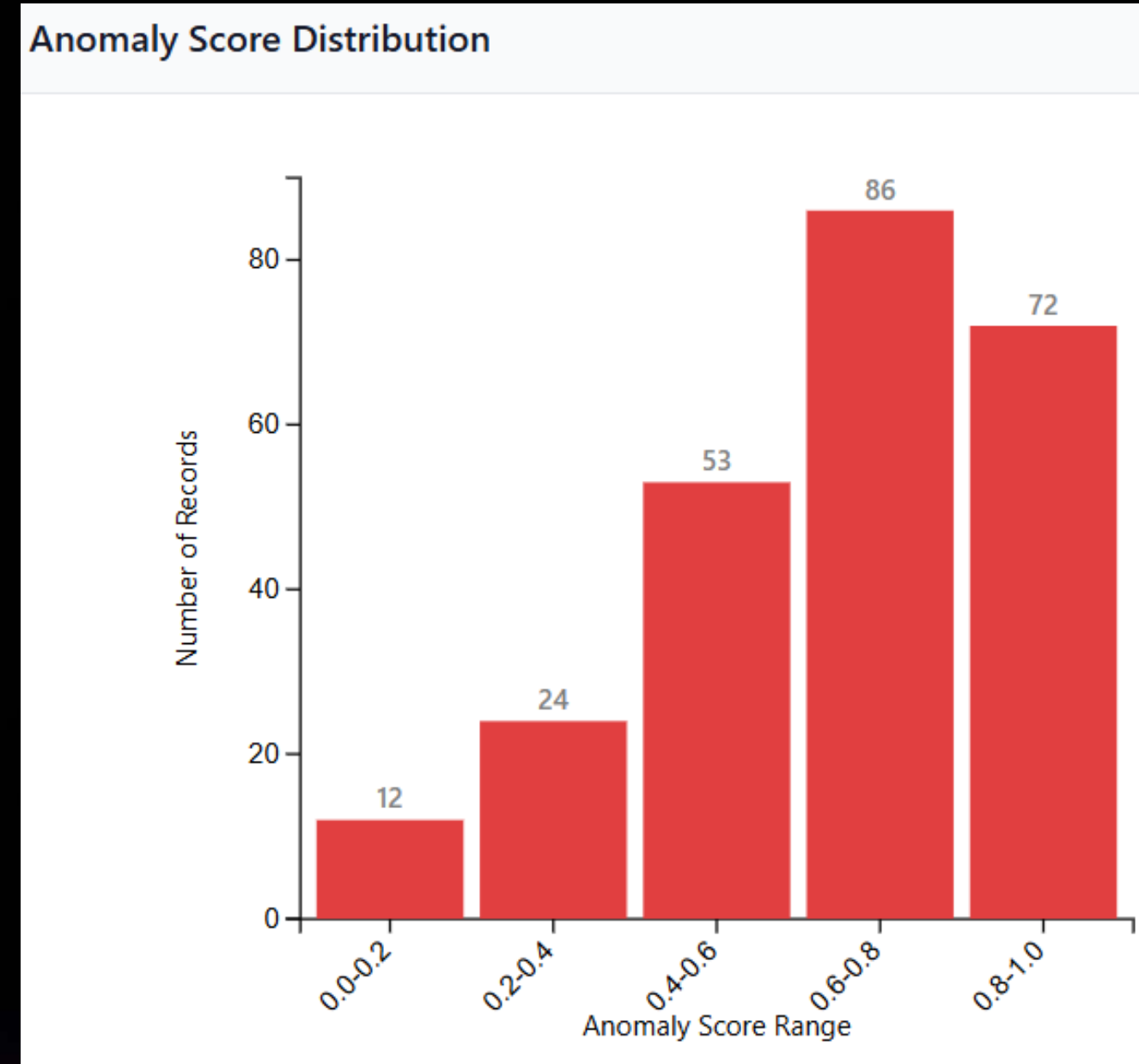
1. Malware
2. Brute Force Attacks
3. Distributed Denial of Service (DDoS)
4. Botnet Activity
5. Data Exfiltration Attempts
6. Denial of Service (DoS)
7. Phishing Attempts
8. Port Scanning Activities

All major types of network anomalies were effectively identified and classified.



Anomaly Score Distribution:

- Records were distributed across various anomaly score ranges.
- The majority of anomalies have moderate to high anomaly scores (between 0.4 and 1.0).
- Very few records fall into low anomaly score ranges (below 0.4).
- This distribution reflects the system's strong capability to distinguish between benign and truly malicious activities.

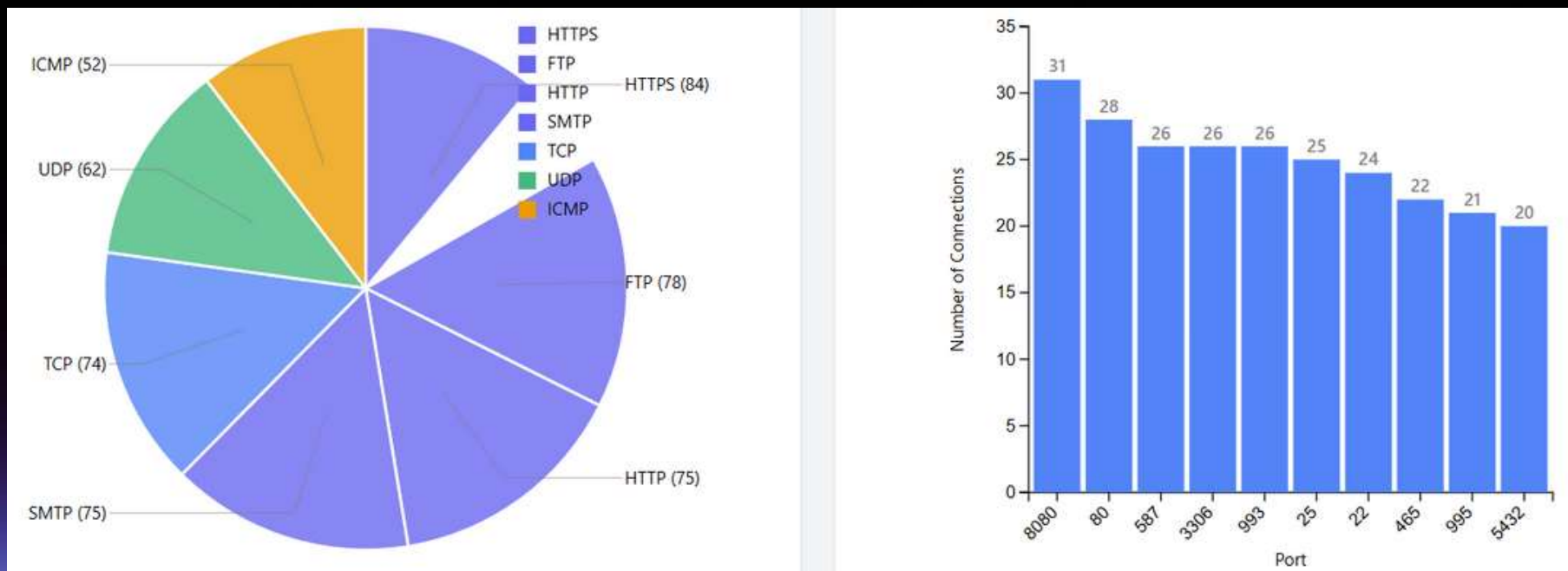


Traffic by Protocol

Network traffic was observed across multiple protocols, including:

- 1.HTTPS
- 2.FTP
- 3.HTTP
- 4.SMTP
- 5.TCP
- 6.UDP
- 7.ICMP

This diversity in protocols highlights a wide variety of network activities, both secure and unsecure.

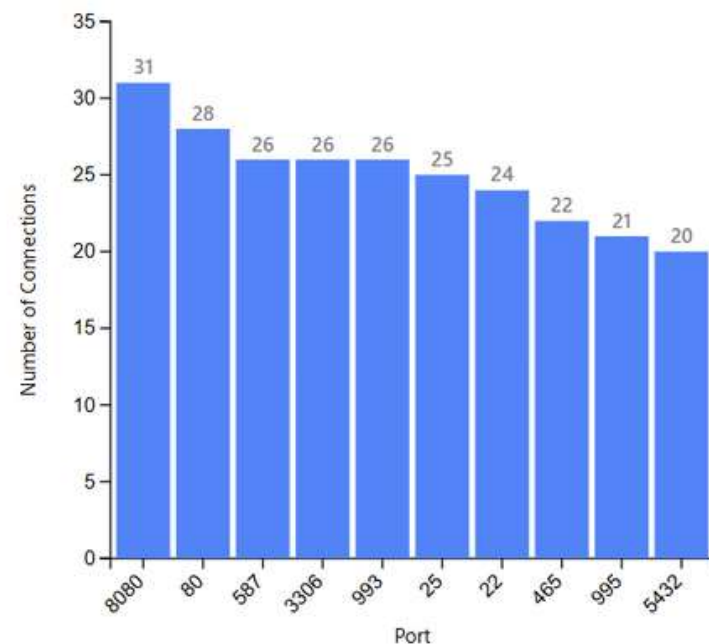


Traffic by Port (Top 10)

Top ports identified in the network flows include:

- 1.8080 (Alternative HTTP port)
- 2.80 (Standard HTTP)
- 3.587 (SMTP Secure Email Submission)
- 4.3306 (MySQL Database)
- 5.993 (IMAP Secure Email Retrieval)
- 6.25 (SMTP Email Transfer)
- 7.22 (SSH Remote Login)
- 8.465 (SMTPS Secure Email Submission)
- 9.995 (POP3 Secure Email Retrieval)
- 10.5432 (PostgreSQL Database)

Traffic across these ports suggests a mix of web services, email communications, database interactions, and secure remote access.



Ensemble Model Architecture

For this project, we used an ensemble model, which combines the strengths of multiple classifiers to improve prediction accuracy and reduce errors. In particular, we used:

- Random Forest (a decision tree-based model) for its strength in handling high-dimensional data.
- XGBoost (a gradient boosting method) to fine-tune the model for better performance.

This combination allows the model to learn from diverse perspectives and make more accurate predictions than individual models alone.

Model Metrics

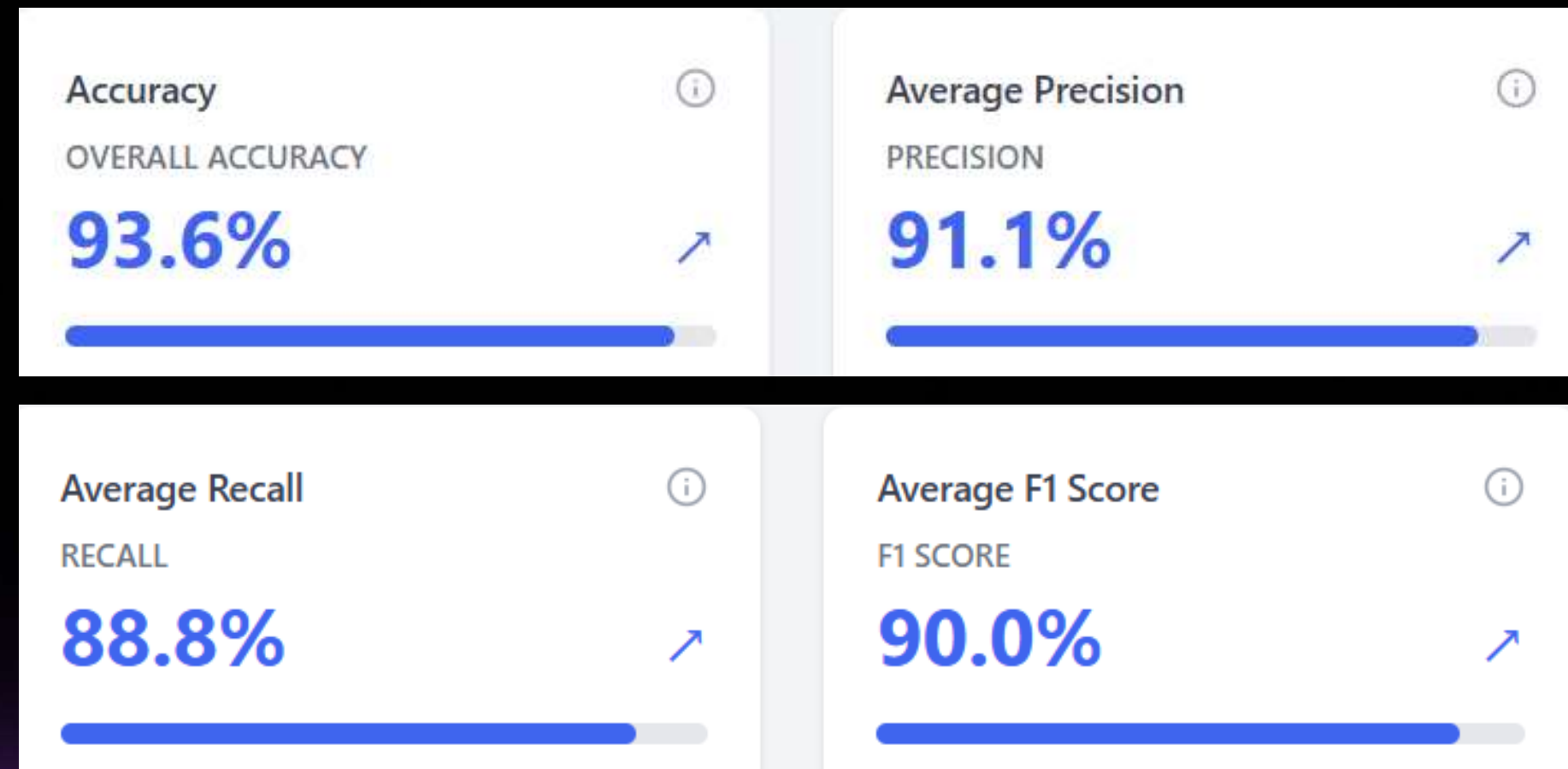
Accuracy:

93.6%

Precision: 91.1%

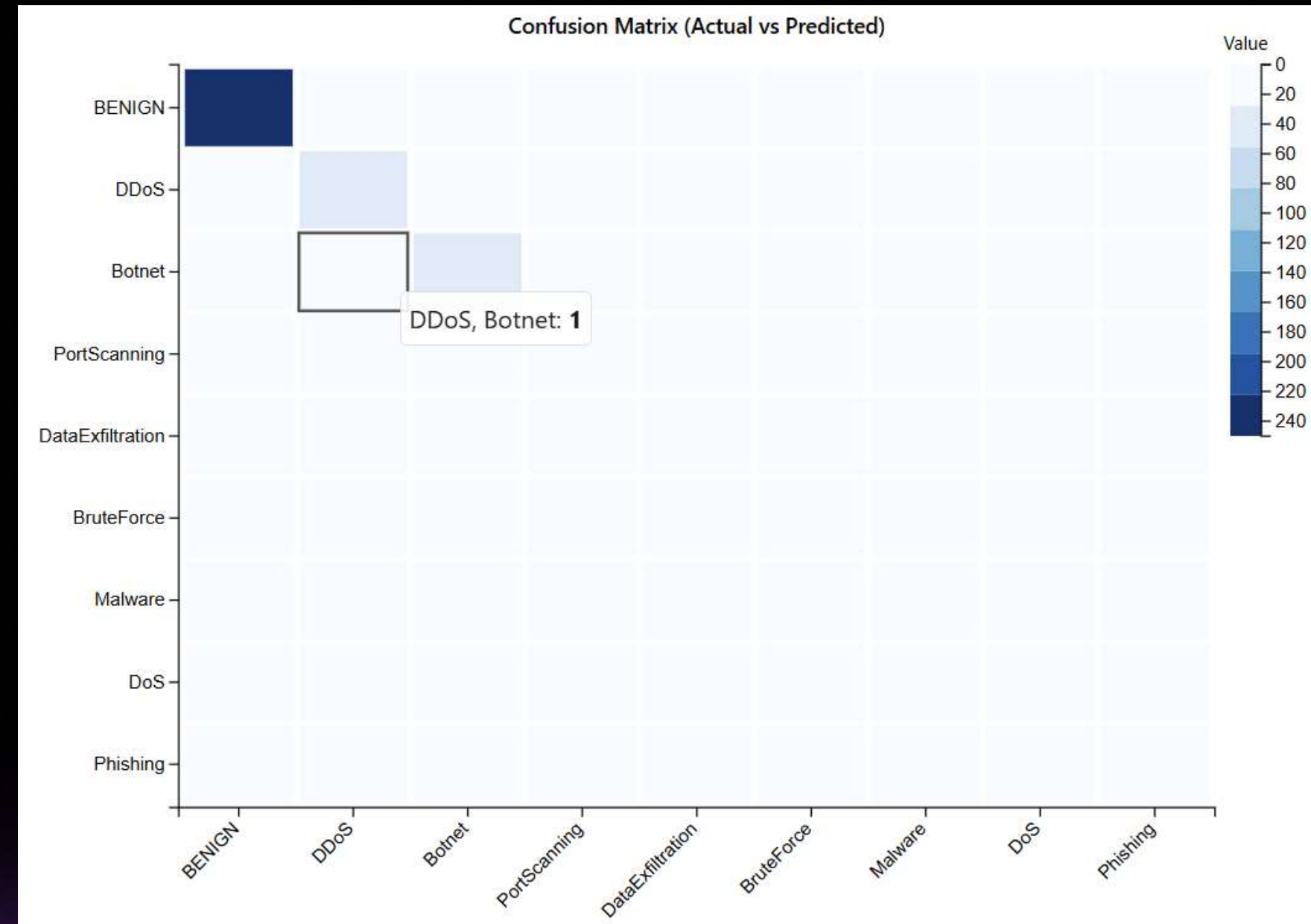
Recall: 88.8%

F1 Score: 90.0%



Confusion Matrix

- The confusion matrix shows how well the model classifies traffic across different categories:
- True Positives: The model correctly identified benign traffic and malicious activities (e.g., DDoS, Malware).
- False Positives: Misclassifications of benign traffic as threats.
- False Negatives: Failure to detect some threats.
- The ensemble model shows strong performance, especially in detecting benign traffic and common attacks like DDoS and Malware.

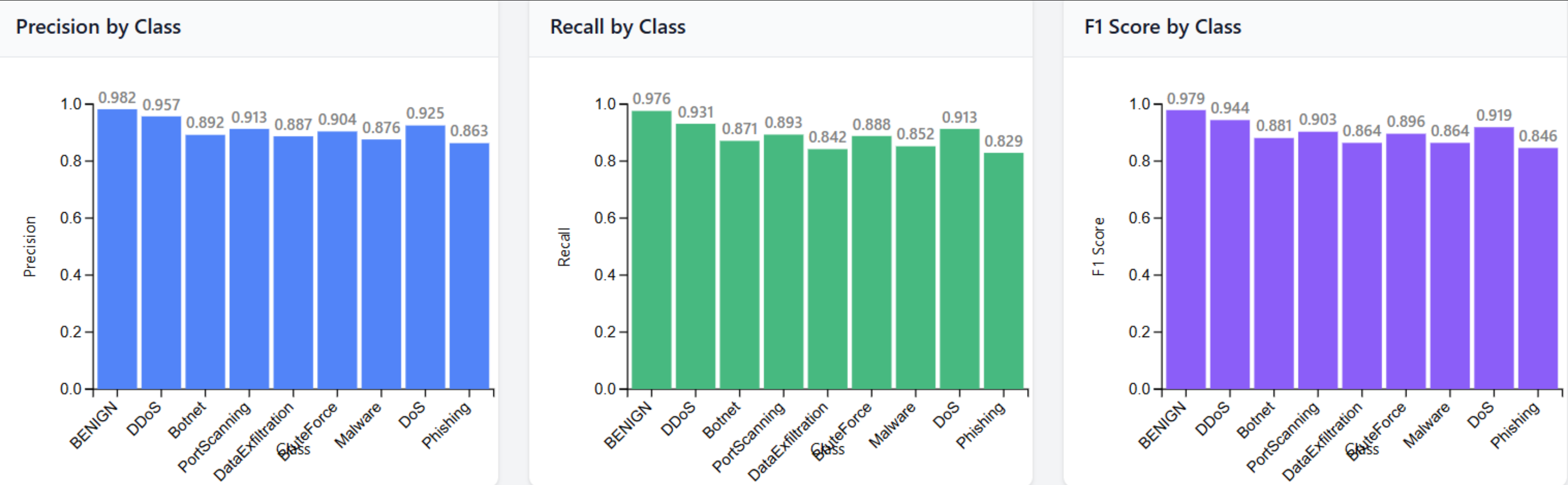


Precision, Recall, and F1 Score by Class:

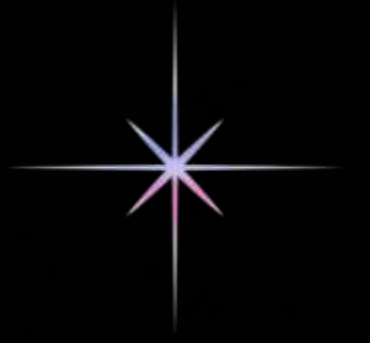
Precision is particularly high for Benign traffic, DDoS, and Botnet traffic, which indicates that the model rarely misclassifies benign traffic or fails to detect malicious activity.

Recall (True Positives) is high across most categories, with Botnet and Port Scanning showing particularly robust detection.

The F1 Score balances the precision and recall to ensure high reliability across all traffic types



Outcomes:



- Automated Network Traffic Analysis using AI/ML models to detect and classify traffic in real time.
- Improved Threat Detection & Security, identifying anomalies, malware, and encrypted attacks with higher accuracy.
- Reduced False Positives & False Negatives, enhancing the efficiency of network security operations.
- Scalability & Performance Optimization, ensuring AI models can handle high-traffic environments with minimal latency.
- Privacy-Preserving Traffic Analysis, leveraging AI for encrypted traffic analysis without decryption.



THANK YOU!