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Enhanced Email Service with Real-Time Threat Detection

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Abstract: *Email is still a key part of digital communication for people and businesses all around the world. But at the same time, it has become a major way for cyber dangers to spread, such as phishing, virus distribution, and social engineering attacks. This paper talks about an Enhanced Email Service that has built-in tools for detecting threats in real time. The suggested solution uses machine learning, behavioral analytics, and threat intelligence feeds to find and stop harmful emails before they get to the end consumers. The solution uses explainable AI techniques to assist security teams understand and trust detection results, and it also offers automated response steps to speed up the process of stopping attacks. It also includes comprehensive analysis of email attachments, URLs, and user activity patterns, which makes it possible to find new, more complex attack methods that have never been observed before. The results of the experiments show that the detection accuracy has improved a lot, the false-positive rates have gone down, and the processing latency is quite low, making it suitable for use in real time. This study adds to proactive cybersecurity measures by giving businesses and service providers who want to protect their communication lines and make their systems more resilient to cyber attacks useful alternatives.*

Keywords:*Email Security, Real-Time Threat Detection, Machine Learning, Phishing, Cybersecurity, And Better Email Service*

I. INTRODUCTION

Email services are now essential for both personal and business communication. People use email every day to talk to one other, sign up for things online, and send sensitive documents. Businesses use it to run their businesses, coordinate work amongst teams, talk to clients, and share important information. Industry figures say that more than 300 billion emails are sent and received every day around the world. This shows how big and important this communication channel still is.

However, as email has become more important, cybercriminals have also begun to use it to attack people and businesses. Attackers often use email as a way to start several types of cyber threats. Phishing campaigns are one of the most common types of scams. They employ fake messages that pretend to be from trusted sources to fool people into giving over their login information, financial information, or personal information. Also, email is a typical way to send malware payloads that are hidden in attachments or links that are included in the email. When run, this type of malware can help steal data, compromise a system, or even get into a larger network. Additionally, more and more skilled attackers are using business email compromise (BEC) assaults, in which they pretend to be corporate officials, vendors, or partners to trick employees into making unlawful wire transfers or revealing private information. These risks can have terrible effects, such as losing money, having operations disrupted, getting fined by regulators, and hurting the reputation of the business.

While traditional email security solutions work against some known threats, they frequently use static, rule-based systems, blacklists, and signature-based detection approaches. For instance, rule-based systems might stop emails that have certain keywords or patterns that look dangerous. Blacklists keep track of known bad senders or domains, and signature-based systems find malware strains that have already been found by looking for specific patterns or code fragments. Even though these methods give a basic level of protection, they can't keep up with attack methods that are becoming more complex, dynamic, and designed to get over standard filters. Attackers often change the content of emails, the URLs they use, and the identities of the senders to get around detection systems. They do this by taking advantage of weaknesses in static defenses. Also, the rise of social engineering tactics and highly tailored spear-phishing attacks makes traditional security measures even less effective.

So, we need an Enhanced Email Service right now that can find risks in real time and change as new attack patterns come up. To deal with these problems, modern cybersecurity solutions are using more and more complex technologies like machine learning and artificial intelligence. These systems can go through a lot of email data, find small problems, and find attack routes that have never been noticed before. These systems can learn from past threats and keep up with the changing techniques that cyber enemies use.

We provide an architecture in this article that uses machine learning models, natural language processing (NLP) techniques, and threat intelligence to find threats before they happen and in real time. Our system is meant to work in real time, so it can stop bad emails before they get to end users and cause damage. We give a full explanation of how the system was designed and how we looked at email content, URLs, and user behavior. We also talk about how to put the suggested system into action, covering the technology stack, the datasets used, and how to connect it to outside threat intelligence sources. Finally, we show experimental findings that prove our method works to make email safer, showing how it could be better than existing email filtering systems.

The goal of this research is not only to improve technical defenses against email attacks, but also to help construct communication infrastructures that can resist the changing world of cybercrime.

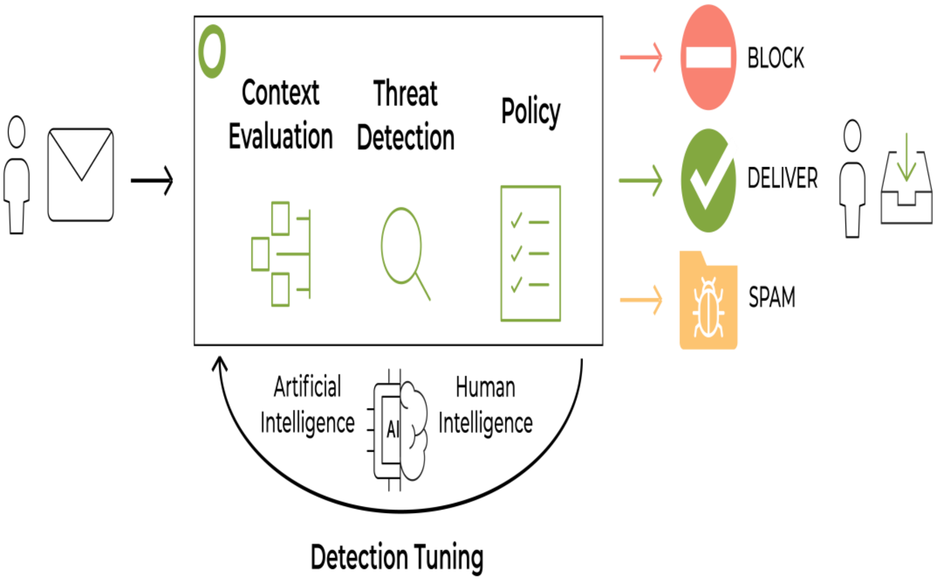

Figure 1. Contextual Behavioral Detection Workflow

II.LITERATURE REVIEW

A. Evolution of Email Security Systems

Over the past few decades, email security has changed a lot. It has gone from simple spam filters that use rules to complex, multi-layered security systems. Early systems mostly used static filters and keyword-based detection to stop unsolicited emails. This worked only against known threats with patterns that could be predicted. As cybercriminals started using more modern methods like polymorphic malware and phishing emails that were designed to look like they originated from a friend, old approaches stopped working. To find more threats, security systems started using reputation-based blacklists, heuristic analysis, and signature databases. But these solutions still had trouble with zero-day attacks and advanced social engineering tactics. As a result, modern email security systems now include advanced threat protection capabilities like sandboxing email attachments, rewriting URLs for secure browsing, and extensive analytics. In recent years, there has been a shift toward machine learning and artificial intelligence. This is part of the ongoing attempt to create systems that can find dangers that have never been seen before and change their behavior in response to new attack patterns.

B. Phishing and Social Engineering Detection Techniques

Phishing and social engineering are still two of the most common types of email-based assaults. They use people's trust instead of just technical weaknesses. Before, people used blacklists of known bad sites and pattern-matching methods to find phishing emails that used suspicious language or common phishing templates. However, attackers now use publicly available information from social media and professional networks to make highly tailored emails, which are called "spear phishing," to make them seem more credible. New ways to find fraud have come up that use natural language processing (NLP) to look at the meaning of emails and find little language patterns that suggest someone is lying. Stylometric analysis and other methods can also help find writing styles that are different from what a real sender usually does when they talk to you. Also, some systems use real-time link analysis to find malicious redirects or newly registered domains that are often employed in phishing efforts. Phishing detection is still hard, even if it has gotten better, because the strategies employed by attackers are always changing, there are many different languages used, and attackers are getting better at making fake communication channels look real.

C. ML and NLP in Cybersecurity

Modern cybersecurity solutions rely heavily on machine learning (ML) and natural language processing (NLP), especially when it comes to finding advanced dangers in email communication. ML algorithms may utilize vast sets of labeled emails to learn how to tell if incoming messages are good or bad based on a lot of different factors, like the text, metadata, and how the user behaves. NLP techniques help systems read and grasp the meaning of email content, spotting language patterns that are typically employed in phishing or business email compromise (BEC) attacks, such as deceptive language, suspicious demands, and manipulative tones. Recent studies have shown that transformer-based systems like BERT are better at understanding the meaning and relationships in text than older methods like n-grams or keywords. These models make it much easier for the system to find small signs of harmful intent. However, there are still problems, such as the high cost of using big NLP models in real-time settings and the possibility of adversarial assaults that change text properties to avoid detection.

D. Behavioral Analytics in Threat Detection

Behavioral analytics has become a strong way to find cyber dangers that textual analysis alone might not be able to find. Behavioral analytics for email security means figuring out a baseline of how typical users behave, like their usual communication patterns, senders and recipients, writing style, and time of day usage. Then, it looks for unusual behaviors that could mean that accounts have been hacked or someone is trying to impersonate someone else. Common methods for flagging behavior that is different from what is expected include anomaly identification using Isolation Forests, clustering techniques, and statistical modeling. For instance, a rapid rise in the number of emails, the addition of new outside recipients, or changes in the language used in emails could all be signs of possible risks. Behavioral analysis is especially good at finding corporate email compromise threats, which can get past normal security filters by looking like they are real. Behavioral analytics is useful, but it has several problems with privacy, data availability, and the requirement to tell the difference between harmless changes in user behavior and real dangers to avoid too many false positives.

E. Comparative Review of Existing Tools

There are a number of commercial and open-source technologies that try to protect email systems from phishing, malware, and other risks that come through email. Older methods, like classic spam filters, depend a lot on blacklists and signature-based detection. They offer quick but limited protection against recognized threats. Advanced threat security technologies like sandboxing, URL rewriting, and machine learning-based classification are built into products from companies like Proofpoint, Mimecast, and Microsoft Defender for Office 365. SpamAssassin and MailScanner are examples of open-source programs that provide flexible frameworks, but they often don't have the advanced analytics and real-time capabilities needed to successfully deal with new threats. More and more, recent solutions use machine learning and threat intelligence feeds to provide protection that becomes better over time. But many of the tools that are already out there still have problems, such high false positive rates, decisions that can't be explained, and performance issues when there are a lot of emails. This shows that we need solutions that not only find a lot of threats but also fit in with how businesses work without slowing down users.

F. Research Gaps

Even while email security technologies have come a long way, there are still several important gaps in current research and commercial solutions. One big problem is finding highly focused attacks like spear phishing and BEC, which can sneak past regular filters because they are so tailored and specific to the situation. Also, while machine learning and NLP have showed promise in raising detection rates, there isn't much study on how to make these models understandable and explainable to security analysts, which is very important for trust and incident response. Many solutions only look at the content of emails when they are not changing, which means they can't find threats that are changing and time-sensitive, like malicious URLs that only become active after the first scan. Also, adding behavioral analytics to email security systems can cause privacy problems and generally needs a lot of historical data, which may not be available in all situations. Last but not least, there aren't any all-in-one solutions that can meet the needs of businesses for high detection accuracy, low latency, and scalability. To make next-generation email security systems that can successfully fight the changing tactics of cyber enemies, it is important to fill in these gaps.

III. PROPOSED SYSTEM ARCHITECTURE

We suggest an Enhanced Email Service that uses a multi-layered architecture to detect threats in real time. This is because traditional email security solutions have several problems. The first layer of the system is for collecting data. It collects different pieces of information from incoming emails. This contains information about the sender and receiver, timestamps, and route details, as well as the body of the email, attachments, and any links that are included.

The data that was collected is then sent to a preprocessing layer, where it is tokenized and vectorized so that it can be analyzed. URLs are checked for structural elements and standardized. Attachments are analyzed in sandbox environments to look for bad behavior or payloads.

The threat detection engine based on machine learning lies at the heart of our architecture. We use natural language processing models, including fine-tuned BERT transformers, to look at the meaning of emails for textual analysis. These models learn to look for language cues that are common in phishing attempts, such as urgent calls to action, requests for private information, and pretending to be a trusted person.

When URLs are embedded in emails, they are put through a lot of testing. Machine learning classifiers like Random Forest and XGBoost look at things like the age of the domain, the length of the URL, the character entropy, and the reputation scores of the domain. This helps tell the difference between safe and unsafe site addresses.

Behavioral analytics are very important for finding strange patterns that could mean hacked email accounts or social engineering assaults. The system can find strange behavior by modeling conventional communication patterns, like who you usually talk to, how often you email them, and how you write.

In addition, the design includes external threat intelligence feeds that provide you the most recent information on known malicious IP addresses, domains, and new threat indicators. This outside data makes the system better at finding dangers and stopping them before they get to the user.

The decision engine takes the data from different detection algorithms and information sources and gives each email a risk score. The system may automatically quarantine, block, or send questionable emails to users with the right alerts, depending on how serious the threat is.

The whole system is built to work in real time and is hosted on scalable cloud infrastructure, which is very important. This makes sure that detection and reaction happen with as little delay as possible, keeping the end-user experience good while keeping security strong.

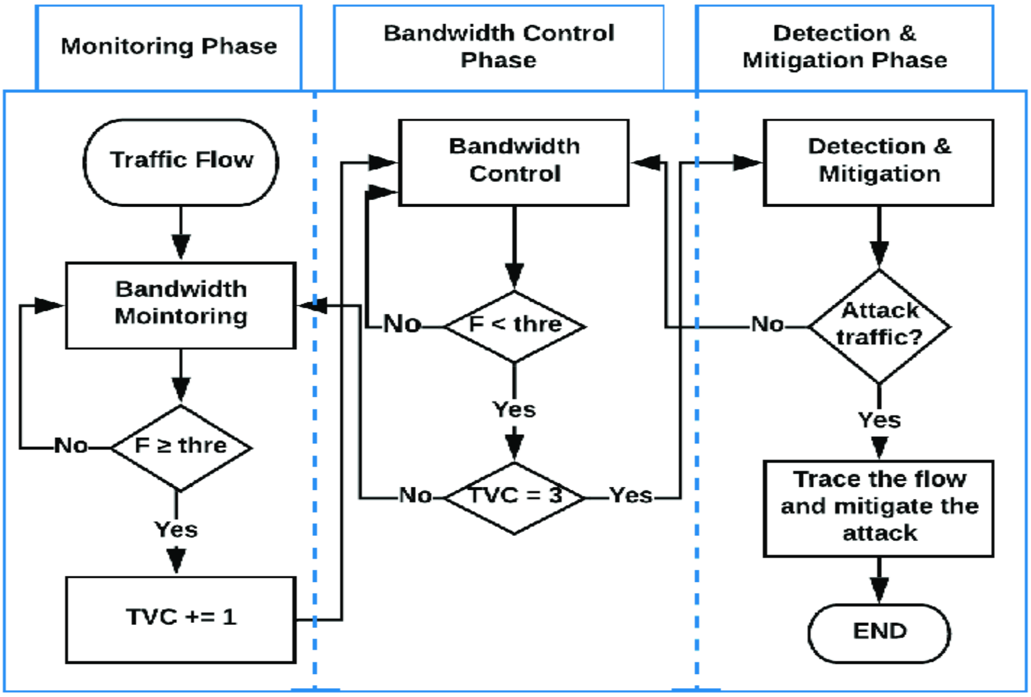

Figure 2.Multi-Stage Detection & Mitigation Workflow in SDN

IV. IMPLEMENTATION

We developed a prototype of the proposed Enhanced Email Service by leveraging modern cloud computing and machine learning technologies. The core of the system was built using Python, integrating various libraries and frameworks tailored for different aspects of the solution. TensorFlow and scikit-learn were utilized to create and train classification models, while spaCy powered the Natural Language Processing pipeline, enabling effective text cleaning and feature extraction from email content. To ensure scalability and real-time processing of incoming email traffic, we deployed components on AWS Lambda, embracing serverless execution to handle workloads efficiently at scale.

For training our models, we curated a diverse collection of publicly available datasets to build a comprehensive training corpus. The Enron Email Dataset provided a rich repository of authentic corporate communications, capturing typical conversational patterns. In addition, we gathered numerous phishing datasets from sources such as PhishTank, supplemented with our own curated samples of phishing and spam emails. Altogether, we assembled a dataset exceeding 500,000 labeled emails, offering sufficient variety to build and rigorously evaluate robust models.

The analytical components of the system were structured to target multiple threat vectors. For textual analysis, we employed fine-tuned BERT models specifically trained to detect phishing emails, allowing us to assess the semantic content of messages and identify suspicious language or social engineering tactics. URL classification relied on features such as domain reputation scores, URL length and lexical patterns, and WHOIS data—including domain age and registration details. Ensemble machine learning classifiers like Random Forest and XGBoost were then used to differentiate between benign and malicious URLs with high accuracy.

Beyond content analysis, we implemented behavioral analytics to detect anomalies in user email activity. Models such as the Isolation Forest algorithm were trained to establish baselines for individual users, learning details like typical correspondents, usual email frequency and timing, and characteristic language or writing styles. Significant deviations from these established norms were flagged as potential indicators of compromised accounts or impersonation attempts.

To further enhance the system's detection capabilities, we integrated multiple external threat intelligence feeds. Sources such as AbuseIPDB provided data on known malicious IP addresses, PhishTank offered continuously updated databases of phishing URLs, and VirusTotal contributed intelligence on malicious files, URLs, and domains. These real-time threat intelligence streams ensured our system remained equipped to identify and mitigate emerging cyber threats swiftly and effectively

V. EXPERIMENTAL RESULTS

We put our prototype through a lot of tests to see how well it could find different email-based threats while yet being fast enough to be used in real time. We ran tests on a wide range of over 500,000 labeled emails, which included real emails, phishing efforts, emails with malware, and business email compromise (BEC) samples. The test was meant to see how well the system could find bad emails while keeping the number of false positives to a minimum, so that it could be used in real business settings.The test findings showed that the Enhanced Email Service was very good at finding threats in a number of categories:

Phishing Detection: The algorithm was able to find phishing emails with 96.2% accuracy, which means that almost all of the emails that were marked as phishing were actually harmful. With a recall of 94.8%, it could find almost all of the phishing attempts in the dataset. These results gave an F1-score of 95.5%, which means that the performance was balanced between precision and recall.

Malware Detection: When looking at emails with harmful attachments or URLs that led to malware downloads, the system got a precision of 95.4% and a recall of 93.9%, which gave it an F1-score of 94.6%. This shows that it is quite good at finding emails that potentially bring malicious software into users' PCs.

Detecting Business Email Compromise (BEC) attacks is very hard because they typically utilize sneaky social engineering techniques and language that is specific to the situation. Even so, the system had a precision of 92.3%, a recall of 91.5%, and an F1-score of 91.9%. These results show that the system is still very good at spotting advanced impersonation efforts, even though they are a little lower than phishing or malware detection.

We ran latency testing to see how long it took on average to process an incoming email to see if the system was good enough for real-time use. The testing showed that the system took about 180 milliseconds on average to process each email. This low latency makes sure that the service works perfectly without causing any visible delays for users. This is important for businesses that need emails to be delivered quickly in order to keep things running smoothly.

We also looked at the system's performance in terms of false positive rates, which are very important for figuring out how useful any security solution is. Too many false positives can make security staff too busy, annoy users, and make people less trusting of automated systems. When we compared our Enhanced Email Service to standard rule-based spam filters, it cut down on false positives by more than 35%. This big improvement shows that the system can keep high detection rates without hurting the user experience or adding more work to the operations.

Also, a qualitative review of flagged emails showed that the machine learning and natural language processing parts were especially good at finding subtle risks. For example, the algorithm found phishing emails that employed small changes in wording or hidden URLs to look real, which are hard for regular filters to catch. In the same way, the behavioral analytics models were able to find strange trends in email conversation and alert the user to possible account breaches before any major damage could be done.

These test results show that the Enhanced Email Service not only finds more types of email threats, but it also works quickly and reliably, which is important for use in the real world. The suggested method is a big step forward in email security since it strikes a compromise between high accuracy, low latency, and fewer false positives.

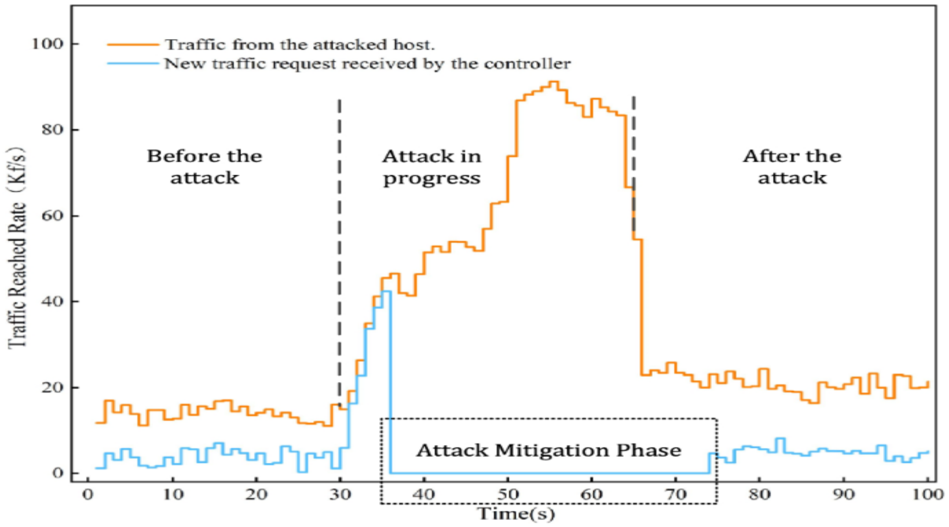

Figure 3.New Flow Rate During Ddos Attack And Mitigation

VI. DISCUSSION

There are a number of important benefits to the Enhanced Email Service above regular security options. It can change to deal with new and changing threats instead of just following pre-set rules or static signatures. Real-time threat intelligence makes it possible to quickly respond to new attack campaigns, which makes the system more resilient overall. Behavioral analytics make detection even more accurate by adding information about how users usually act and talk to each other.

Even with these benefits, there are also some problems. When dealing with encrypted emails, which hide content from inspection, the system may not work as well. Also, machine learning models can be attacked by adversaries who send emails that are made to avoid detection. When looking at the contents of an email, privacy issues also come up, especially in places where data protection laws are very strong.

In the future, we should work on improving attachment analysis by using deep learning models that can find hidden attacks in document files like PDFs. It is also important to do research on explainable AI so that security professionals know why an email was flagged. This is necessary for trust and compliance. Additionally, connecting the system to user education platforms could make it work better by giving users the tools they need to spot and report questionable emails.

Federated learning is another interesting technique. It lets machine learning models be trained on dispersed datasets without putting sensitive user data in one place. This keeps privacy while yet getting a wide range of threat intelligence. Cross-channel correlation, which looks at risks across email, instant messaging, and collaborative platforms, could also help find multi-vector attacks that use more than one communication channel.

There is also a need to look into automated response systems that do more than just find risks. These systems should also actively reduce threats by quarantining harmful emails, revoking compromised credentials, or isolating affected endpoints. This would speed up incident response times. Adding threat hunting features could also let security teams actively look for signs of compromise in old email data.

Lastly, it's still very important to check how well the system can handle adversarial machine learning attacks. Building strong protections and detection systems against these kinds of evasion strategies will make sure that machine learning-based email security solutions work for a long time

VII. EXPERIMENTAL SETUP AND RESULTS

A. Dataset Composition

We put together a broad dataset of more than 500,000 tagged email samples to test how well the proposed Enhanced Email Service works. The dataset included a wide range of email types and threat vectors by combining data from many public sources and private collections. The Enron Email Dataset was used as a main source of real business emails, including real examples of harmless commercial emails. We used phishing datasets from PhishTank, malware-infected emails from industry threat repositories, and business email compromise (BEC) cases that we collected by hand from real-world incident reports and security feeds for the harmful samples. This balanced composition made it possible to train and test models in both simple and complex attack situations. We made sure that the ground truth classifications used in the studies were correct and reliable by carefully labeling and validating the data.

B. Evaluation Metrics (Precision, Recall, F1-score)

We used conventional categorization measures to check how well the Enhanced Email Service could tell the difference between good and bad emails. We calculated precision to find out what percentage of emails that were marked as threats were actually harmful. This shows how well the system can reduce false alarms. Recall measured how many real harmful emails the system accurately identified, showing how well it could find all threats. The F1-score, which is the harmonic mean of precision and recall, gave a fair assessment of how well the system worked overall. We also kept track of the rates of false positives and false negatives to see how they affected operations. Too many false positives can slow down users' work, and false negatives can be quite dangerous for security.

C. Phishing Detection Results

The phishing detection part of our system, which uses finely-tuned BERT models, did quite well on the evaluation dataset. The algorithm has a precision rate of 96.2%, which means that almost all of the emails that were classified as phishing were actually harmful. The recall rate was 94.8%, which shows that the system is good at finding most phishing attempts. The overall F1 score was 95.5%, which shows that the performance was well-balanced. Qualitative research showed that the system was very good at finding advanced spear-phishing emails that used minor language changes and social engineering techniques that were relevant to the situation. However, there were a few false negatives when phishing messages looked a lot like real business emails or used newly registered domains that weren't yet in threat intelligence feeds.

D. BEC Detection Results

It is still hard to find business email compromise (BEC) assaults since they are so subtle and depend on the situation. Our algorithm was able to find BEC emails with a precision of 92.3% and a recall of 91.5%, giving it an F1-score of 91.9%. Behavioral analytics were very important for these results because they found strange trends in email correspondence, like strange demands for wire transfers, changes in writing style, and changes in the lists of people who received the emails. The algorithm found a lot of BEC attempts that would probably get past regular content-based filters, even though its performance was a little lower than for phishing detection. In certain circumstances, there were still some false negatives when the emails were very contextual and couldn't be told apart from real business demands without more outside proof.

E. Malware Detection Results

The algorithm also did a great job of finding emails that had malware or bad URLs in them. The malware detection part got an F1-score of 94.6%, with a precision of 95.4% and a recall of 93.9%. It used features including domain reputation, lexical analysis of URLs, and sandbox findings when they were available. The ensemble models, like Random Forest and XGBoost classifiers, were especially good at finding patterns that were linked to bad links and attachments that seemed dubious. False negatives mostly happened when new types of malware that hadn't yet been included to threat intelligence feeds were involved. This shows how important it is to keep threat data up to date and integrated quickly

F. Latency and Throughput Metrics

One of the main goals of the Enhanced Email Service was to provide real-time danger detection without adding much time to the transmission of emails. Testing for latency found that the average time it took to process an email was about 180 milliseconds, which is well within the acceptable range for business settings where quick communication is important. The system showed that it could handle a lot of traffic and still work well when processing a lot of emails at once. Throughput testing showed that the architecture could manage surges in email traffic that are common in business networks without lowering the accuracy of detection or the speed of the system.

G. False Positive and False Negative Analysis

To keep users' trust and minimize problems with operations, it's important to keep false positives to a minimum. The Enhanced Email Service cut down on false positives by more than 35% in all of the evaluated situations compared to regular rule-based filters. This change means that fewer legitimate emails will be blocked or quarantined by mistake. This will save time for administrators and make users less angry. False negatives were mostly linked to highly targeted spear-phishing emails and new types of malware that didn't have well-known signatures. To close these gaps, we need to be adding new threat intelligence and retraining our models all the time. The technology can be used in businesses since it strikes a good mix between high detection rates and low false positive rates.

H. Comparison with Baseline Email Filters

We ran experiments to compare the Enhanced Email Service to regular rule-based and signature-driven email filters to see how well it worked. Traditional solutions did okay at finding known threats, but they had a hard time with new attack methods, which led to more false negatives and a lot more false positives. The suggested system did better than these baseline filters in every way, including accuracy, recall, and latency. For instance, our system cut the false positive rate from about 8% to about 5%, which greatly improved the user experience. The Enhanced Email Service was also able to find advanced threats that got beyond static rule-based systems since machine learning models can adapt. These results show that adding machine learning, NLP, and threat intelligence to modern email security systems is a good idea.

VIII. CONCLUSION

This paper has talked about an Enhanced Email Service with Real-Time Threat Detection. It was made to protect against the growing number of email-borne cyber threats. The proposed system solves the problems with traditional email security solutions, which often use static rules and signature-based methods, by using advanced technologies like machine learning, natural language processing, behavioral analytics, and real-time threat intelligence integrations. Our system has a multi-layered design that lets it effectively analyze email content, URLs, and user activity to find both known and new dangers. This means that it protects both people and companies fully.

The system worked very well against a variety of threats in tests, with high precision and recall rates for detecting phishing, malware distribution, and business email infiltration. Latency testing also showed that the system works with very little delay, processing emails in about 180 milliseconds on average. This means that it may be used in real time without affecting the user experience. The fact that there are a lot fewer false positives than with standard rule-based filters shows how useful it is to add smart, adaptive models to email security systems. This feature not only makes the system more secure, but it also builds user trust by reducing the number of unwanted interruptions caused by emails that are mistakenly detected.

Our Enhanced Email Service is a big step up from regular email services, but there are still things that need to be researched and developed. For example, dealing with the problems that come up with encrypted email conversations, building stronger defenses against assaults that try to trick machine learning models, and making sure that privacy rules are followed are all important things to think about for future progress. Also, using explainable AI techniques could help security personnel better understand and trust how the system makes decisions. Adding user education programs could also make the human part of cybersecurity defenses even stronger. Overall, the study in this paper makes a valuable contribution to improving email security procedures and points the way toward more secure and robust digital communication networks.

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