

CHAPTER - 1.INTRODUCTION

You've laid out a clear and concise introduction to the problem of spam and the motivation for using Recurrent Neural Networks (RNNs), particularly LSTMs, for its classification. Let's enrich this background information to provide a more comprehensive understanding of the challenges and the potential of deep learning in this domain.

BACKGROUND AND MOTIVATION

The pervasive nature of email as a primary communication tool in both personal and professional spheres has unfortunately made it a fertile ground for malicious activities, most notably spamming. The sheer volume of emails exchanged daily underscores the scale of the problem, where billions of messages traverse digital networks, a significant portion of which are unsolicited bulk emails, commonly known as spam.

The Growing Menace of Spam:

Spam emails are more than just an inbox clutter; they represent a significant threat to individuals and organizations alike:

- **Nuisance and Productivity Loss:** The constant influx of unwanted emails wastes users' time as they sift through and delete spam, hindering productivity and causing frustration.
- **Security Risks:** Spam often serves as a vector for serious security threats, including:
 - **Phishing Attacks:** Deceptive emails designed to trick recipients into revealing sensitive information such as passwords, credit card details, or personal identification numbers.¹ These attacks can lead to identity theft and financial losses.

1. www.bitdefender.com

www.bitdefender.com

- **Malware Distribution:** Spam emails can contain malicious attachments or links that, when clicked, can install viruses, ransomware, spyware, or other harmful software on the user's device, compromising data and system integrity.
- **Scams and Fraud:** Spam is frequently used to perpetrate various scams, including financial scams, fake investment opportunities, and fraudulent prize claims, leading to financial exploitation of unsuspecting individuals.
- **Network Strain and Resource Consumption:** The massive volume of spam emails consumes significant network bandwidth and storage resources, impacting the efficiency of email servers and internet infrastructure.

Limitations of Traditional Email Filtering Systems:

Early email filtering systems relied heavily on manually defined rules based on known characteristics of spam emails (e.g., specific keywords, suspicious sender addresses, or unusual email structures). While these rule-based systems provided an initial layer of defense, they suffer from several limitations:

- **Inflexibility and Difficulty in Maintaining:** Spammers constantly adapt their techniques to evade rule-based filters. Maintaining and updating these rules requires continuous effort and expert knowledge to identify and incorporate new spam patterns.
- **Inability to Handle Novel Spam:** Rule-based systems are often ineffective against new and previously unseen spam tactics, leading to a constant cat-and-mouse game between filter developers and spammers.
- **High False Positive Rates:** Overly aggressive rules can sometimes misclassify legitimate emails as spam (false positives), leading to important communications being missed.
- **Lack of Contextual Understanding:** Traditional rule-based systems typically analyze individual features in isolation and lack the ability to understand the contextual meaning of the email content.

Machine learning algorithms offered an improvement over rule-based systems by learning patterns from labeled data. Techniques like Naive Bayes, Support Vector Machines (SVMs), and decision trees have been widely used for spam classification. These methods often rely on features extracted from the email content, such as word frequencies, presence of specific terms, and statistical properties of the text. However, they still have limitations:

- **Dependence on Feature Engineering:** The performance of these models heavily relies on the quality and relevance of the manually engineered features. Identifying the most effective features can be challenging and requires significant domain expertise.
- **Limited Ability to Capture Long-Range Dependencies:** Traditional machine learning models often treat emails as a collection of independent features, failing to capture the crucial sequential relationships between words that contribute to the overall meaning and context. This limits their ability to detect sophisticated spam that relies on nuanced language or narratives.

The Promise of Deep Learning and Recurrent Neural Networks (RNNs):

The advent of deep learning has brought significant advancements in various fields, including Natural Language Processing (NLP). Recurrent Neural Networks (RNNs), a class of neural networks designed to process sequential data, have shown remarkable success in tasks that require understanding the order and dependencies within a sequence, such as language translation, sentiment analysis, and text generation.

RNNs for Enhanced Spam Classification:

RNNs are particularly well-suited for spam classification due to their ability to:

- **Process Sequential Data:** Emails are inherently sequential, with the meaning of words often depending on the words that precede and follow them. RNNs can process emails word by word, maintaining an internal state that captures information about the sequence encountered so far.

- **Learn Contextual Information:** By considering the sequence of words, RNNs can learn the contextual meaning of words and phrases, enabling them to differentiate between legitimate communication and spam that might use similar vocabulary but in a deceptive context.
- **Model Long-Range Dependencies:** Standard RNNs can struggle with very long sequences due to the vanishing gradient problem. However, variants like Long Short- Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) have been specifically designed to overcome this limitation, allowing them to effectively learn and retain information over long sequences of text, which is crucial for understanding the context of an entire email.

Focus on Long Short-Term Memory (LSTM) Networks:

Long Short-Term Memory (LSTM) networks are a powerful type of RNN architecture that introduces memory cells and gating mechanisms (input gate, output gate, and forget gate). These gates regulate the flow of information into and out of the memory cell, allowing the LSTM to selectively remember relevant information over long sequences and forget irrelevant information. This capability makes LSTMs particularly well-suited for tasks like spam classification, where the context of words far apart in the email can be critical for accurate classification.

By leveraging the power of LSTM networks, our proposed system aims to overcome the limitations of traditional spam filtering techniques by automatically learning complex patterns and long-range dependencies in email text, leading to a more accurate, robust, and adaptable solution for combating the ever-evolving threat of spam

CHAPTER – 2:LITERATURE SURVEY

1. ***"Email Spam Classification: A Review"*** by K. M. Mahbubul Alam, M. M. A. Hashem, and A. Al Mamun. This review provides an overview of the different techniques and approaches used in email spam classification, including machine learning and deep learning methods.
2. ***"Spam Detection: A Machine Learning Perspective"*** by S. K. S. Gupta. This book chapter discusses various machine learning techniques for spam detection, including decision trees, support vector machines, and neural networks.
3. ***"Spam Filtering Techniques: A Review"*** by A. O. Ayoade and O. O. Olabiyisi. This project reviews the different approaches to spam filtering, including rule-based filtering, content-based filtering, and collaborative filtering.
4. ***"Spam Detection using Machine Learning Techniques: A Review"*** by M. M. Rashid, M. M. A. Hashem, and A. Gani. This review discusses the application of machine learning techniques such as decision trees, naïve Bayes, and support vector machines for spam detection.
5. ***"A Survey of Email Spam Detection Techniques"*** by A. A. Bhuyan, J. Kalita, and D. K. Bhattacharyya. This survey project provides an overview of the different spam detection techniques, including content-based filtering, header-based filtering, and behavioral analysis.
6. ***"Spam Filtering: An Overview"*** by G. S. Mankotia and R. Bhatia. This project provides an overview of the challenges and techniques involved in spam filtering, including machine learning, text mining, and natural language processing.

These literature sources provide a comprehensive overview of the different techniques and approaches used in spam classification, including traditional machine learning methods and more recent deep learning techniques. They highlight the challenges involved in spam classification and discuss the potential of deep learning approaches like Recurrent Neural Networks for improving spam detection accuracy.

CHAPTER – 3: SYSTEM ANALYSIS

3.1 EXISTING SYSTEM: Traditional Approaches to Spam Classification

Current email filtering systems have historically relied on a combination of rule-based systems and traditional machine learning techniques to identify and classify spam emails. These methods analyze various aspects of an incoming email to determine its legitimacy.

Rule-Based Systems:

As mentioned earlier, these systems employ a set of predefined rules created by human experts. These rules can look for specific keywords (e.g., "free money," "urgent action"), patterns in email headers (e.g., suspicious sender domains, missing information), or unusual email structures.

Traditional Machine Learning Approaches:

When machine learning is employed, it typically involves:

- **Feature Engineering:** Experts manually identify and extract relevant features from the email content, sender information, and metadata. These features are then used to train a machine learning model. Examples of such features include:
 - Bag-of-Words (BoW) or TF-IDF (Term Frequency-Inverse Document Frequency): Representing the email content as a vector based on the frequency of words, often ignoring the order of words.
 - Presence of Specific Keywords: Binary features indicating whether certain spam-related keywords are present in the email body or subject.
 - Sender Reputation: Features based on the sender's IP address, domain, or historical behavior.
 - Email Header Analysis: Features related to the "From," "To," "Subject," and other header fields, looking for inconsistencies or suspicious patterns.
 - URL Analysis: Features related to the URLs present in the email body, such as the domain name, length, or presence on blacklists.
 - Statistical Features: Measures like the number of capital letters, punctuation marks, or the ratio of text to HTML.

- **Classification Algorithms:** Various machine learning algorithms are trained on these engineered features to learn the patterns that distinguish spam from legitimate emails. Common algorithms include:
 - Decision Trees: Tree-like structures that classify emails based on a series of decisions based on the feature values.
 - Support Vector Machines (SVM): Algorithms that find an optimal hyperplane to separate spam and legitimate emails in a high- dimensional feature space.
 - Naive Bayes Classifiers: Probabilistic models that classify emails based on the likelihood of the features given the class (spam or not spam), assuming independence between features.
 - Logistic Regression: A linear model that predicts the probability of an email being spam.
 - K-Nearest Neighbors (KNN): Classifies an email based on the majority class among its k nearest neighbors in the feature space.

DRAWBACKS OF EXISTING SYSTEMS: Enhanced Detail

While these traditional approaches have provided a foundational level of spam filtering, they suffer from several significant limitations in the face of increasingly sophisticated spamming techniques:

1. Limited Feature Representation: A Bottleneck to Accuracy

- **Loss of Semantic Information:** Representing text as a bag of words or using simple keyword presence ignores the crucial semantic relationships between words and the overall meaning of the email. Two emails with the same set of words but in different orders can have drastically different meanings, which these models often fail to capture.
- **Inability to Capture Nuances and Context:** Spam emails often employ subtle linguistic cues, persuasive language, or social engineering tactics that are difficult to capture with handcrafted features. The context in which words are used is often lost, hindering the model's ability to identify deceptive content.

- **Dependence on Expert Knowledge and Tedious Engineering:** The process of identifying and engineering effective features requires significant domain expertise and can be a time-consuming and iterative process. As spamming techniques evolve, new features need to be manually designed and incorporated, which can be a constant struggle to keep up.
- **Failure to Generalize to Unseen Patterns:** Manually crafted features are often designed based on known spam patterns. When spammers introduce new techniques or obfuscation methods, these features may become ineffective, leading to poor generalization performance on unseen spam.

2. Difficulty in Handling Sequential Data: Missing the Narrative

- **Ignoring Word Order and Dependencies:** Language is inherently sequential, and the order of words significantly impacts the meaning. Traditional machine learning models often treat words as independent entities, failing to capture the dependencies and relationships between them that form the context of the email. For example, the phrase "urgent account verification" might be a strong indicator of phishing, but a bag-of-words model would treat these words individually, potentially missing the critical sequential pattern.
- **Suboptimal Performance on Context-Dependent Spam:** Sophisticated spam emails often build a narrative or use a sequence of persuasive arguments to trick users. Models that cannot understand these sequential patterns are less likely to identify such nuanced spam.
- **Inability to Learn Long-Range Context:** The context relevant for classifying an email as spam might span across multiple sentences or even the entire email body. Traditional models often struggle to capture these long-range dependencies, limiting their ability to understand the overall intent and identify subtle indicators of malicious content.

3. Scalability Issues: Struggling with the Ever-Increasing Volume

- **Computational Bottlenecks with High-Dimensional Feature Spaces:** As the volume of emails increases, the number of features used in traditional machine learning models can also grow, leading to high dimensional feature spaces. Training and applying these models can become computationally expensive and time-consuming, potentially causing delays in email processing.
- **Inefficient Processing of Large Datasets:** Traditional machine learning algorithms might not scale efficiently to handle the massive datasets required to train robust spam classifiers in the face of billions of daily emails. This can lead to longer training times and slower model updates.
- **Increased Latency in Real-Time Filtering:** In real-time email filtering systems, speed is crucial. Traditional models, especially more complex ones with a large number of features, might introduce unacceptable latency in classifying incoming emails, impacting user experience.
- **Maintenance and Resource Intensive Updates:** Adapting to new spamming techniques often requires retraining the models on new data and potentially re-engineering features. This process can be computationally expensive and require significant resources and time.

In conclusion, while traditional methods have played a crucial role in combating spam, their reliance on manual feature engineering, inability to effectively handle sequential data, and potential scalability issues make them increasingly inadequate in the face of the evolving and sophisticated nature of spam emails. This necessitates the exploration of more advanced techniques like Recurrent Neural Networks (RNNs) that can overcome these limitations.

3.2 PROPOSED SYSTEM: Enhanced Spam Classification with Recurrent Neural Networks

Building upon the limitations of traditional machine learning, our proposed system leverages the power of Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, to achieve more accurate and context-aware spam classification. The inherent ability of LSTMs to model sequential data and capture long-range dependencies makes them exceptionally well-suited for understanding the nuanced context within email content, a crucial aspect often missed by conventional methods.

Our proposed system comprises the following essential stages:

1. Comprehensive Email Data Preprocessing:

This initial phase is critical for transforming raw email data into a structured and numerically representable format that the LSTM network can effectively process. This involves several key steps:

- **Tokenization:** The process of breaking down each email into individual words or sub-word units (tokens). This step essentially converts the continuous text into a sequence of discrete elements. For example, the sentence "This is a spam email." would be tokenized into ["This", "is", "a", "spam", "email", "."]. Advanced tokenization techniques might also handle punctuation and special characters in specific ways.
- **Stop Word Removal:** Common words that often carry little semantic meaning (e.g., "the," "a," "is," "are") are identified and removed. This helps to focus the model's attention on more informative words that contribute significantly to the email's content and context.

- **Text Normalization:**

This may involve several techniques to standardize the text:

- **Lowercasing:** Converting all text to lowercase (e.g., "Spam" becomes "spam") to ensure consistency and reduce the vocabulary size.
- **Stemming/Lemmatization:** Reducing words to their root form (stemming) or dictionary form (lemma) to treat variations of the same word as a single entity (e.g., "running," "runs," and "ran" might be reduced to "run"). Lemmatization is generally more sophisticated as it considers the word's meaning in context.
- **Conversion to Numerical Representations (Word Embeddings):** This is a crucial step where each unique token is mapped to a dense vector of real numbers. These vectors, known as word embeddings, capture the semantic relationships between words. Words that are semantically similar are located closer to each other in the embedding space. Popular techniques for generating word embeddings include:

- **Word2Vec (Skip-gram and CBOW):** These models learn embeddings by predicting a target word given its context or vice versa from a large corpus of text.
- **GloVe (Global Vectors for Word Representation):** GloVe leverages global word co-occurrence statistics to learn word embeddings.
- **FastText:** This method extends Word2Vec by considering subword information, allowing it to handle out-of-vocabulary words more effectively.
- **Pre-trained Embeddings:** Utilizing pre-trained embeddings (e.g., from large text corpora like Wikipedia or Common Crawl) can significantly improve performance, especially when the training dataset for spam classification is relatively small. These embeddings capture general semantic knowledge learned from vast amounts of text data.

2. Training an LSTM Neural Network:

The core of our proposed system is an LSTM neural network. LSTMs are a type of RNN specifically designed to handle the vanishing gradient problem, which often hinders the ability of standard RNNs to learn long-range dependencies. The unique architecture of LSTM units, featuring memory cells and gates (input, output, and forget gates), allows them to selectively remember or forget information over long sequences, making them ideal for understanding the context of an entire email.

- **Network Architecture:** The LSTM network will likely consist of one or more LSTM layers. The input to the first LSTM layer will be the sequence of word embeddings representing the preprocessed email. Subsequent LSTM layers can learn higher-level abstractions from the sequential information. The output of the final LSTM layer will typically be fed into one or more dense (fully connected) layers.
- **Output Layer:** The final dense layer will have a single output unit with a sigmoid activation function. This output will represent the probability that the input email is spam (e.g., a value close to 1 indicates a high probability of being spam, while a value close to 0 indicates a low probability).
- **Training Process:** The LSTM network will be trained on a large, labeled dataset of emails, where each email is tagged as either "spam" or "not spam" (ham).

- **Loss Function:** The network's performance during training is evaluated using a loss function that quantifies the difference between the predicted probability and the actual label. For binary classification (spam/not spam), a common choice is the binary cross-entropy loss. The goal of training is to minimize this loss function.
- **Optimization Algorithm:** An optimization algorithm, such as Adam or RMSprop, will be used to update the network's weights during training to minimize the loss function. These algorithms iteratively adjust the weights based on the gradients of the loss with respect to the weights.
- **Hyperparameter Tuning:** The performance of the LSTM network is highly dependent on its hyperparameters, such as the number of LSTM layers, the number of units in each layer, the embedding dimension, the learning rate, and the batch size. Techniques like cross-validation and grid search or more advanced optimization methods can be employed to find the optimal hyperparameter settings.

3. Evaluation and Deployment:

Once the LSTM network is trained, its performance will be evaluated on a separate, unseen test dataset to assess its generalization ability. Key evaluation metrics for spam classification include:

- **Accuracy:** The percentage of correctly classified emails.
- **Precision:** The proportion of emails predicted as spam that are actually spam.
- **Recall (Sensitivity):** The proportion of actual spam emails that are correctly identified as spam.
- **F1-Score:** The harmonic mean of precision and recall, providing a balanced measure of the model's performance.
- **Area Under the ROC Curve (AUC):** A measure of the model's ability to distinguish between spam and not spam across different classification thresholds.

Upon satisfactory evaluation, the trained LSTM model can be deployed for real-time spam classification of incoming emails. This might involve integrating the model into an email server or client application.

By leveraging the sequential modeling capabilities of LSTMs and employing careful preprocessing techniques, our proposed system aims to significantly improve the accuracy and effectiveness of spam classification, addressing the

limitations of traditional methods that often struggle with the contextual nuances and evolving nature of spam emails.

ADVANTAGES OF THE PROPOSED SYSTEM

The adoption of Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks, in our proposed spam classification system offers significant advantages over traditional machine learning approaches:

1. Superior Sequence Modeling and Contextual Understanding:

- **Capturing Long-Range Dependencies:** Unlike traditional methods that often treat emails as a bag of words, ignoring the sequential nature of language, RNNs excel at processing sequential data. LSTMs, with their specialized memory cells and gating mechanisms, are particularly adept at capturing long-range dependencies within the email text. This means the model can understand how words appearing earlier in the email can influence the meaning and classification of words appearing much later. For instance, an LSTM can recognize that a seemingly innocuous phrase early in an email might gain a malicious context when combined with later content, something a bag-of-words model would likely miss.
- **Understanding Semantic Relationships and Context:** By considering the order of words, LSTMs can better grasp the semantic relationships between them and the overall context of the email. This is crucial for identifying sophisticated spam tactics that rely on subtle linguistic cues or narratives that unfold over the course of the email. For example, an LSTM can learn to differentiate between a legitimate request and a phishing attempt that might use similar initial phrasing but diverge later in the message.
- **Handling Variable Length Sequences:** Emails can vary significantly in length. RNNs are inherently designed to handle input sequences of variable lengths, processing each email as a sequence of words without requiring artificial padding or truncation that can lead to information loss. This allows the model to effectively analyze both short, concise spam messages and longer, more elaborate phishing attempts.

2. Automatic and Adaptive Feature Learning:

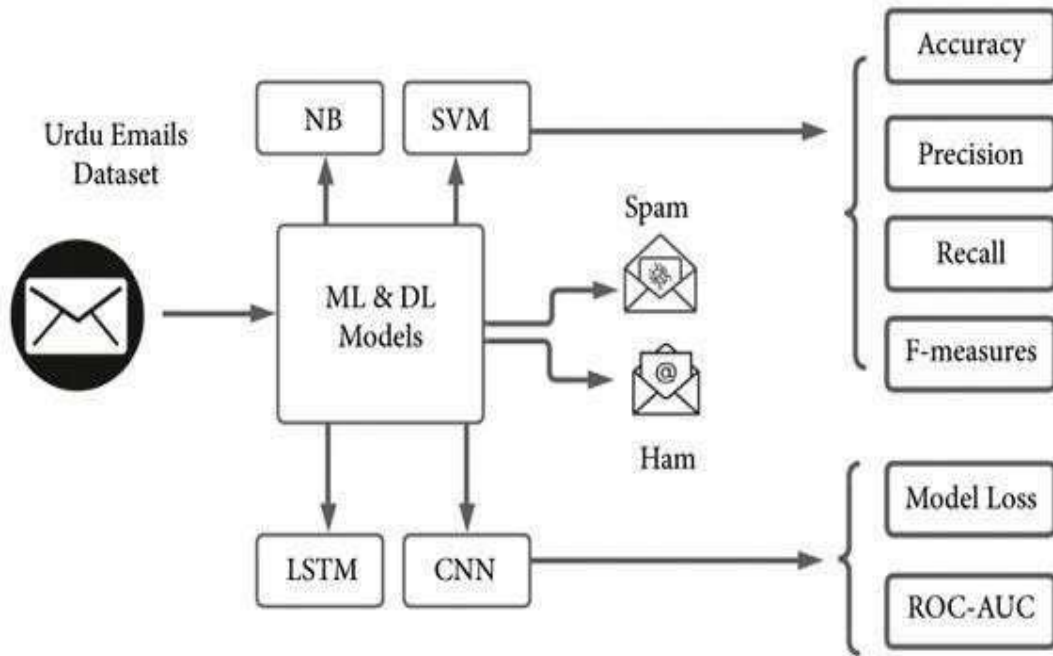
- **Eliminating Manual Feature Engineering:** Traditional machine learning models often rely on manually crafted features extracted from the email content (e.g., presence of certain keywords, email header

information, URL characteristics). This feature engineering process is time-consuming, requires domain expertise, and might not generalize well to new types of spam. RNNs, on the other hand, can automatically learn relevant features directly from the raw text data (after preprocessing like tokenization and embedding).

- **Learning Hierarchical Representations:** Deep LSTM networks can learn hierarchical representations of the text. The initial layers might learn low-level features like patterns of characters or words, while deeper layers can learn more abstract and complex features related to the semantic structure and intent of the email. This automatic feature learning allows the model to discover intricate patterns that might be difficult or impossible for humans to manually engineer.
- **Improved Generalization to Novel Spamming Techniques:** Spammers constantly evolve their tactics, making manually engineered features potentially obsolete over time. RNNs, by learning features directly from the data, can adapt to new and unseen spamming techniques more effectively. If new patterns emerge in spam emails, the LSTM model has the potential to learn these patterns during training without requiring explicit updates to the feature engineering process.
- **Reduced Reliance on Domain Expertise for Feature Design:** The automatic feature learning capability reduces the dependence on specific domain expertise for designing effective features. The model learns what features are important for distinguishing spam from legitimate emails directly from the data, potentially uncovering subtle indicators that human experts might overlook.

In essence, the use of LSTMs empowers our proposed system to move beyond surface-level analysis of email content and delve into a deeper understanding of the sequential structure and semantic nuances, leading to a more robust and adaptable spam classification solution. The automatic feature learning capability further streamlines the development process and enhances the system's ability to generalize to the ever-changing landscape of spam.

SYSTEM ARCHITECTURE:



3.3 HARDWARE & SOFTWARE REQUIREMENTS:

HARD REQUIRMENTS:

- System : i3 or i5.
- RAM: 4 GB.
- Hard Disk : 40 GB

SOFTWARE REQUIRMENTS:

- Operating system : Windows8 or Windows 10
- Coding Language : python

CHAPTER – 4:FEASIBILITY STUDY

Ensuring a Viable Project

A feasibility study is a critical initial phase in any project lifecycle. It serves to evaluate the practicality and viability of the proposed system, ensuring that the project is not only technically sound but also economically justifiable and socially acceptable within the organizational context. By conducting a thorough feasibility analysis, potential pitfalls can be identified early on, allowing for informed decision-making regarding project continuation or modification.

The three primary dimensions of feasibility analysis that you've correctly identified are:

1. ECONOMICAL FEASIBILITY: Justifying the Investment

This aspect of the feasibility study focuses on the financial implications of developing and implementing the proposed spam classification system. It aims to determine whether the potential benefits of the system outweigh the costs associated with its development, deployment, and maintenance.

- **Cost Analysis:** A detailed breakdown of all anticipated costs is essential:
 - **Research and Development (R&D) Costs:** This includes the time and effort of the development team (data scientists, machine learning engineers, software developers), resources used for experimentation, and any costs associated with exploring different RNN architectures and preprocessing techniques. While you mentioned leveraging freely available technologies, the labor costs associated with expertise in these areas are significant.
 - **Software and Hardware Costs:** While core deep learning libraries (like TensorFlow or PyTorch) and programming languages (like Python) are open-source, there might be a need for specialized hardware, especially for training complex deep learning models. This could include high-performance GPUs or cloud computing resources. Consider the costs of setting up and maintaining the necessary infrastructure.
 - **Data Acquisition and Preparation Costs:** If the available labeled email dataset is insufficient, there might be costs associated with acquiring more data or the effort involved in labeling and cleaning large volumes of email data.
 - **Integration and Deployment Costs:** Integrating the developed system with existing email infrastructure and deploying it in a

production environment will incur costs related to system configuration, testing, and potential modifications to existing systems.

- **Training and Documentation Costs:** Developing training materials and conducting training sessions for users (as mentioned in social feasibility) will have associated costs.
- **Maintenance and Support Costs:** Ongoing maintenance, bug fixes, model retraining (as spam patterns evolve), and technical support will be recurring expenses.
- **Potential Licensing Costs:** While the core technologies might be free, any specialized tools or libraries required for integration or monitoring might have licensing fees.
- **Benefit Analysis:** Quantifying the potential benefits of the new system is crucial for justifying the investment:
 - **Increased Productivity:** By more effectively filtering spam, users will spend less time dealing with unwanted emails, leading to increased productivity. Quantifying this in terms of saved employee hours can demonstrate significant cost savings.
 - **Reduced Security Risks:** A more accurate spam filter can reduce the likelihood of successful phishing attacks and malware distribution, potentially preventing significant financial losses and reputational damage. Estimating the potential cost of a security breach can highlight the value of an improved system.
 - **Improved User Experience:** A cleaner inbox leads to a better user experience and increased satisfaction with the email system. While harder to quantify financially, this can have positive indirect impacts.
 - **Reduced IT Support Costs:** A more effective system might reduce the number of spam-related issues reported to IT support.
 - **Compliance and Regulatory Benefits:** In some industries, effective spam filtering might be necessary for compliance with data protection regulations.
- **Return on Investment (ROI):** By comparing the total estimated costs with the total anticipated benefits over a defined period, the economic feasibility can be assessed. A positive ROI indicates that the project is likely to be economically viable.

2. TECHNICAL FEASIBILITY: Assessing Technical Capabilities

This aspect examines whether the organization possesses the necessary technical expertise, infrastructure, and resources to successfully develop, implement, and maintain the proposed RNN-based spam classification system.

- **Technical Expertise:**

- **Data Science and Machine Learning Skills:** The project requires individuals with expertise in deep learning, particularly RNNs and LSTMs, as well as experience in data preprocessing, model training, evaluation, and deployment. Assess if the current team has these skills or if external hiring or training will be necessary.
- **Software Development and Integration Skills:** Integrating the deep learning model with the existing email infrastructure will require skilled software developers.
- **Infrastructure Management:** Expertise in managing the hardware and software infrastructure required to run the model efficiently in a production environment is crucial.

- **Available Infrastructure:**

- **Hardware Resources:** Training deep learning models can be computationally intensive, often requiring access to GPUs. Evaluate the availability of suitable hardware resources, either in-house or through cloud computing platforms. Consider the computational requirements for real-time inference once the model is deployed.
- **Software and Tools:** Assess the availability of necessary software libraries (e.g., TensorFlow, PyTorch, scikit-learn), development environments, and deployment tools.
- **Network Capabilities:** Ensure that the network infrastructure can handle the data flow and processing demands of the new system.

- **Project Complexity and Risk:**

- **Novelty of the Approach:** Implementing a deep learning-based system for spam classification might be a relatively new endeavor for the organization. Assess the inherent risks associated with adopting a potentially complex technology.
- **Data Availability and Quality:** The success of a deep learning model heavily depends on the availability of a large, high-quality

labeled dataset. Evaluate the current data resources and the effort required for data preparation.

- **Integration Challenges:** Integrating a new system with existing email infrastructure can present technical challenges. Assess the potential complexities of this integration.
- **Scalability and Performance:** The developed system must be able to handle the increasing volume of emails and provide timely classification results without significant performance degradation. Evaluate the potential scalability of the proposed architecture.

3. SOCIAL FEASIBILITY: Ensuring User Acceptance

This aspect focuses on the human factors involved in the deployment of the new system. It assesses the likelihood of users accepting and effectively utilizing the proposed spam classification system.

- **User Acceptance and Impact:**
 - **Perceived Benefits:** Users need to understand how the new system will benefit them (e.g., reduced spam, less risk of phishing). Clearly communicating these benefits is crucial for gaining acceptance.
 - **Ease of Use:** The system should ideally operate transparently without requiring significant changes in user behavior. If user interaction is required (e.g., for reporting misclassified emails), the process should be intuitive and user-friendly.
 - **Potential Disruption:** Assess if the new system will cause any significant disruptions to users' workflows. Minimizing disruption is key to smooth adoption.
 - **Addressing Concerns:** Users might have concerns about the accuracy of the new system (e.g., fear of legitimate emails being marked as spam). Addressing these concerns proactively and providing mechanisms for feedback and error correction is important.
- **Training and Support:**
 - **Training Requirements:** Determine the level of training required for users to understand how the new system works and how to interact with it (if necessary). Develop effective training materials and delivery methods.

- **Ongoing Support:** Plan for ongoing technical support to address user issues and answer questions related to the new system.
- **Organizational Culture and Change Management:**
 - **Resistance to Change:** Assess the organization's culture and the potential for resistance to adopting a new technology. Implementing effective change management strategies can help mitigate this resistance.
 - **Stakeholder Involvement:** Involving users and other stakeholders in the development and implementation process can increase their sense of ownership and improve acceptance.
- **Ethical Considerations:**
 - **Bias in Data:** Ensure that the training data is representative and does not contain biases that could lead to unfair or discriminatory classification.
 - **Transparency and Explainability:** While deep learning models can be complex, providing some level of transparency or explainability regarding why an email was classified as spam can increase user trust.

By thoroughly analyzing these three key aspects of feasibility – economic, technical, and social – you can gain a comprehensive understanding of the viability of your proposed RNN-based spam classification system and make informed decisions about its development and implementation. Remember that a well-conducted feasibility study can save significant time, resources, and potential setbacks in the long run.

CHAPTER – 5: SYSTEM DESIGN

5.1 UML DIAGRAMS: Visualizing Software Architecture

Unified Modeling Language (UML) stands as a cornerstone in modern software engineering, offering a standardized, general-purpose visual modeling language. Its creation and ongoing management by the Object Management Group (OMG) underscore its industry-wide recognition and importance.

UML: A Common Language for Software Blueprints:

The fundamental goal of UML is to provide a consistent and readily understandable language for creating models of object-oriented computer software. Think of UML as the blueprint for software systems, allowing developers, designers, and stakeholders to visualize, specify, construct, and document the various aspects of a software project in a standardized way. This visual representation facilitates better communication, reduces ambiguity, and helps in understanding the complexity of software systems.

The Core Components of UML:

In its current form, UML primarily comprises two essential components:

- **Meta-model:** This defines the abstract syntax and semantics of the UML. It essentially specifies the concepts, relationships, and rules that govern how UML models are constructed. The meta-model acts as the underlying foundation, ensuring consistency and a shared understanding of the modeling language itself. It defines the types of UML elements (like classes, objects, interactions, states) and how they can be interconnected.
- **Notation:** This provides the graphical symbols and syntax used to visually represent the elements defined in the meta-model. The notation is what users see and interact with when creating UML diagrams. These diagrams use a standardized set of icons, lines, and text to depict different aspects of the software system, such as its structure, behavior, and interactions.

The Potential Evolution of UML:

You mentioned that in the future, some form of method or process might be added to or associated with UML. While UML itself is primarily a modeling language (focused on *what* to model), its application is often guided by specific software development methodologies (focused on *how* to develop software), such as Agile, Scrum, or Waterfall. Integrating or more closely associating UML with these methodologies could provide more prescriptive guidance on how to effectively use UML throughout the software development lifecycle.

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You mentioned that in the future, some form of method or process might be added to or associated with UML. While UML itself is primarily a modeling language (focused on *what* to model), its application is often guided by specific software development methodologies (focused on *how* to develop software), such as Agile, Scrum, or Waterfall. Integrating or more closely associating UML with these methodologies could provide more prescriptive guidance on how to effectively use UML throughout the software development lifecycle.

UML: Beyond Software - Applications in Business Modeling:

It's important to highlight that the utility of UML extends beyond just software systems. Its ability to model complex systems makes it valuable for business modeling and other non-software domains. For instance, UML can be used to model business processes, organizational structures, and workflows, providing a visual and structured way to understand and analyze these systems.

UML: A Synthesis of Best Practices:

The UML isn't just an arbitrary collection of symbols; it represents a culmination of best engineering practices that have proven successful in the modeling of large and complex systems over time. It incorporates concepts and techniques from various object-oriented modeling approaches, aiming to provide a comprehensive and effective toolkit for system design.

The Indispensable Role of UML in Object-Oriented Development:

As you correctly pointed out, UML is a very important part of developing object-oriented software and the overall software development process. Its emphasis on graphical notations makes it accessible and facilitates communication among team members with different technical backgrounds. By providing a common visual language, UML helps to:

- **Visualize System Design:** UML diagrams offer a clear and concise visual representation of the software's architecture, making it easier to understand the relationships between different components.
- **Specify System Requirements:** UML can be used to model user interactions and system behavior, helping to clearly define and document system requirements.
- **Facilitate Communication:** The standardized notation ensures that all stakeholders have a common understanding of the system's design.
- **Aid in Design and Development:** UML models serve as a blueprint during the design and development phases, guiding the implementation process.

- **Document System Architecture:** UML diagrams provide valuable documentation of the system's structure and behavior, which is essential for maintenance, understanding, and future development.

GOALS OF UML Design: Empowering Effective Modeling

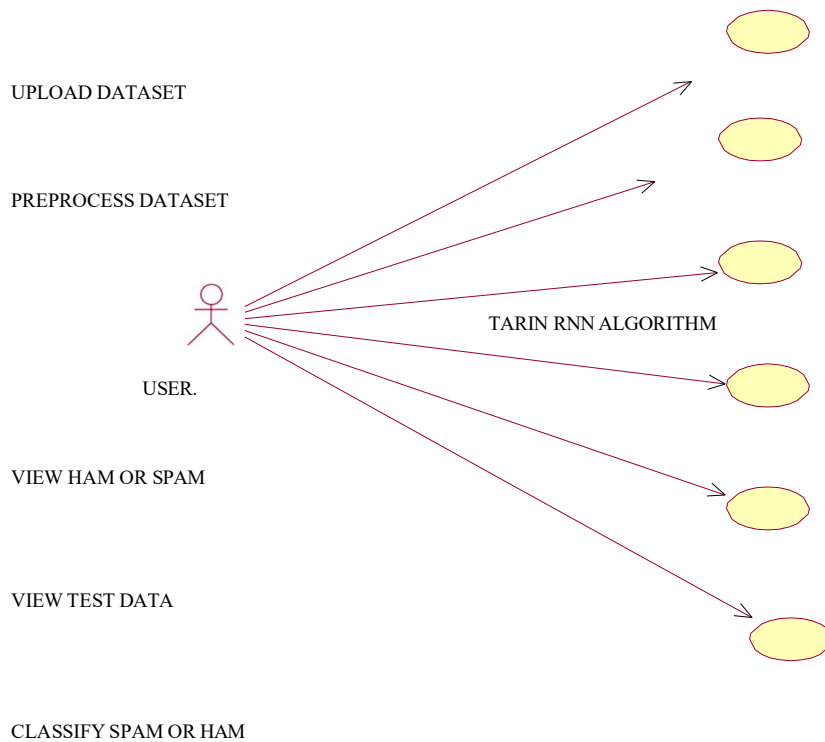
The primary goals in the design of the UML underscore its commitment to providing a powerful, flexible, and widely applicable modeling language:

1. **Providing a Ready-to-Use, Expressive Visual Modeling Language:** This emphasizes the practical utility of UML. It aims to offer a language that is immediately applicable and provides a rich set of visual constructs to model various aspects of a system effectively and meaningfully. The focus is on expressiveness, allowing modelers to capture complex relationships and behaviors clearly.
2. **Providing Extendibility and Specialization Mechanisms:** Recognizing that no single language can perfectly fit every domain or specific need, UML is designed to be extensible. Mechanisms like stereotypes, tagged values, and profiles allow users to adapt and specialize the core UML concepts to address the unique requirements of their particular application domain or development process.
3. **Being Independent of Particular Programming Languages and Development Process:** UML strives for neutrality. It is designed to be a language for modeling the *conceptual* design of a system, independent of the specific programming language that will be used for implementation (e.g., Java, Python, C#) or the chosen software development methodology. This allows UML models to be valuable across different technology stacks and development approaches.
4. **Providing a Formal Basis for Understanding the Modeling Language:** The underlying meta-model provides a formal semantic foundation for UML. This formal basis ensures that the meaning of UML constructs is well-defined and unambiguous, facilitating better understanding and interpretation of models, as well as enabling the development of robust modeling tools.
5. **Encouraging the Growth of OO Tools Market:** By providing a standardized and widely adopted modeling language, UML fosters the development of a robust market for object-oriented modeling tools. These tools provide graphical editors, model validation, code generation, and other features that enhance the efficiency and effectiveness of software development.

6. **Supporting Higher Level Development Concepts:** UML is designed to support advanced object-oriented concepts such as collaborations (how objects interact to achieve a specific goal), frameworks (reusable design structures), patterns (proven solutions to recurring design problems), and components (modular and replaceable parts of a system). This allows developers to model complex system architectures effectively.
 7. **Integrating Best Practices:** UML incorporates and reflects many of the best practices in object-oriented design and modeling that have evolved over years of experience in the field. By using UML, developers are implicitly guided towards adopting these proven and effective modeling techniques.
- In essence, UML provides a powerful and versatile toolkit for visualizing, specifying, constructing, and documenting software systems (and even business processes). Its standardized notation, formal foundation, and support for advanced concepts make it an indispensable tool in modern software engineering, fostering better communication, design, and overall software quality.

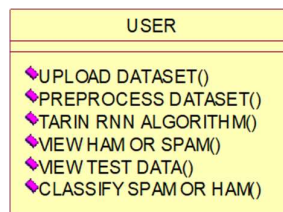
5.2 USE CASE DIAGRAM:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.



5.3 CLASS DIAGRAM:

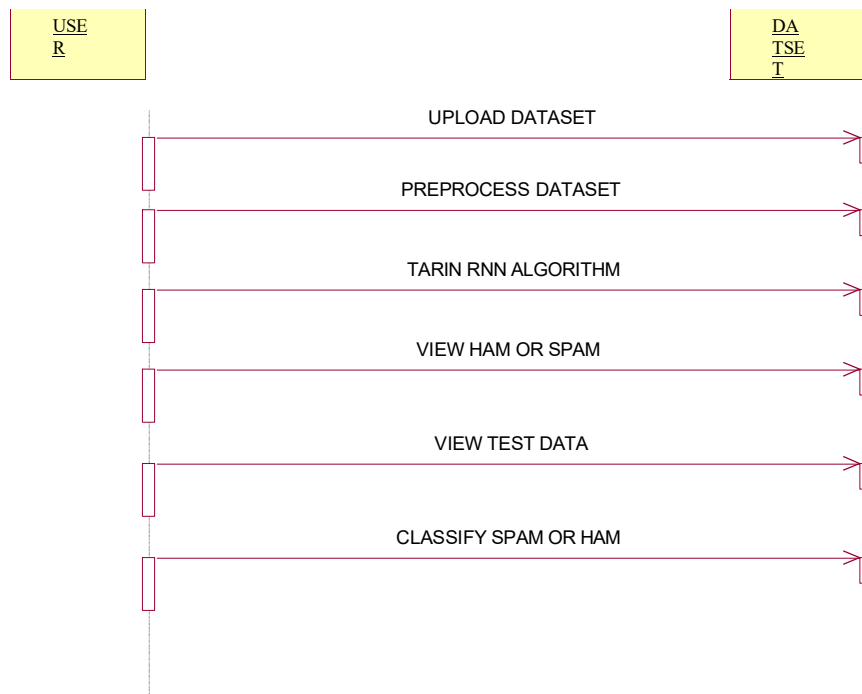
In software engineering, a class diagram in the Unified Modeling



Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.

5.4 SEQUENCE DIAGRAM:

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.



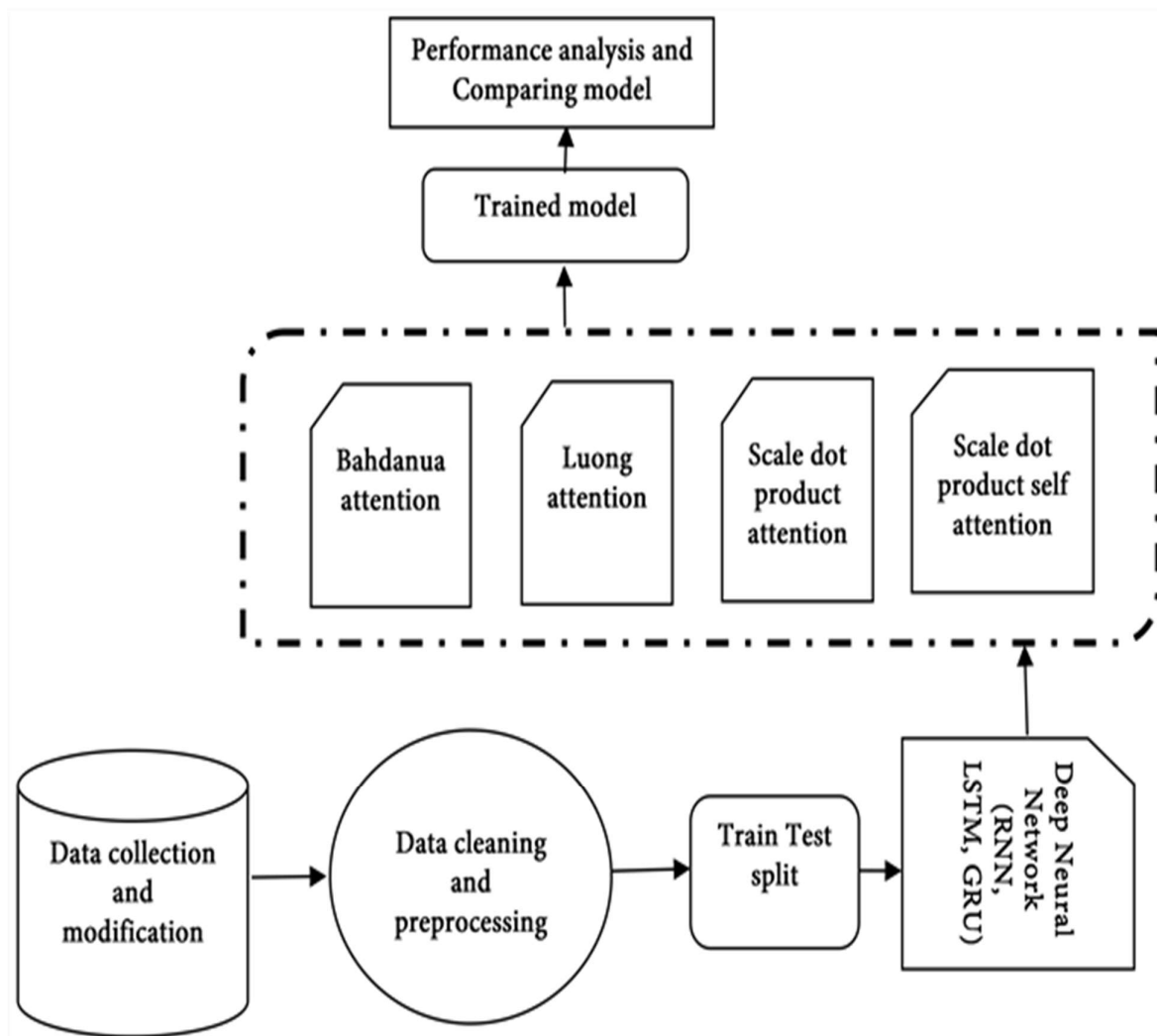
5.1 ACTIVITY DIAGRAM:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

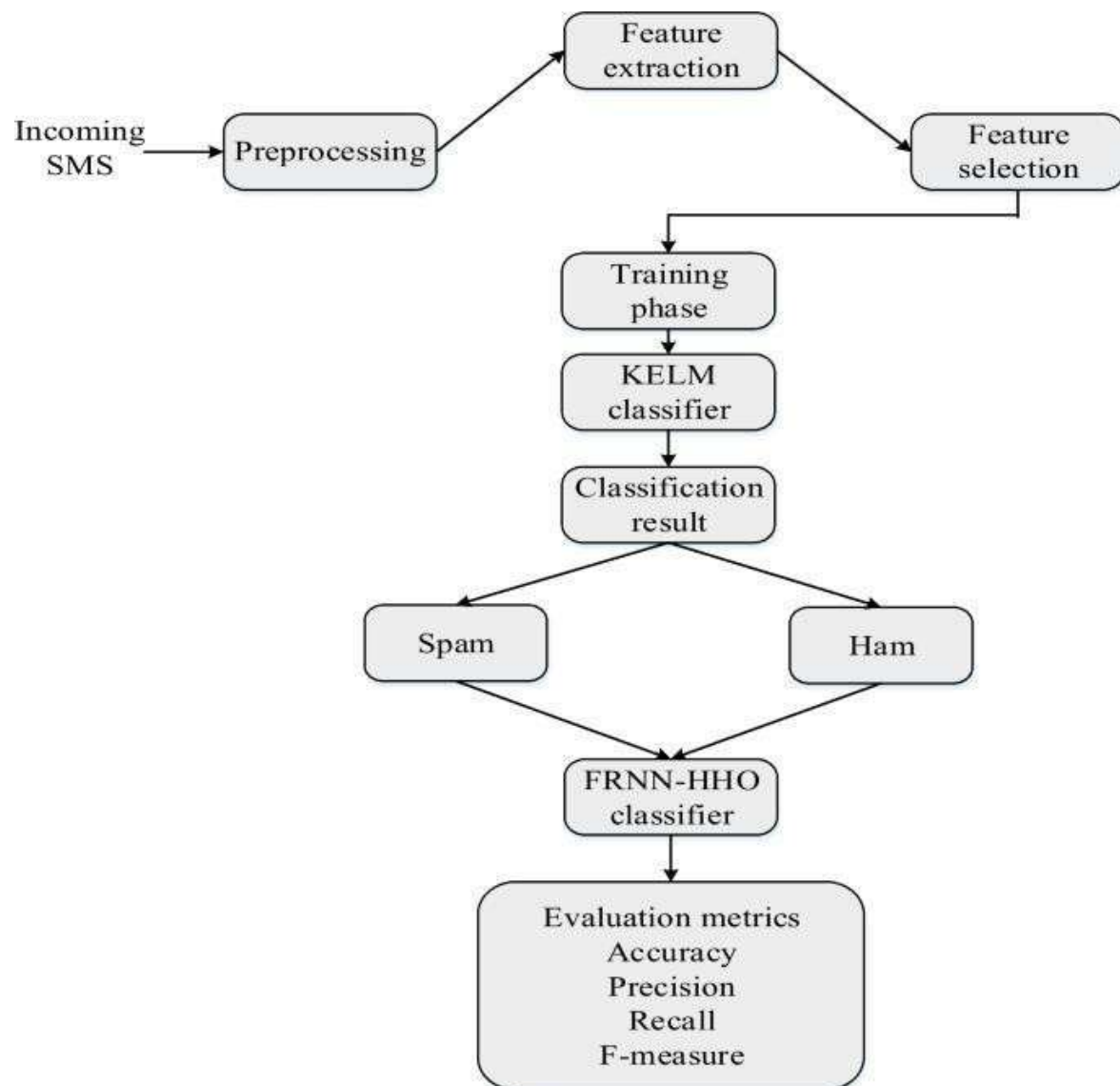
- 1: UPLOAD DATASET
- 2: PREPROCESS DATASET
- 3: TARIN RNN ALGORITHM
- 4: VIEW HAM OR SPAM
- 5: VIEW TEST DATA
- 6: CLASSIFY SPAM OR HAM



5.2 DATA FLOW DIAGRAM:



5.3 ACTIVITY DIAGRAM:



5.4 Designing the Input and Output: Quantum-Resistant Secure Email

The design of the input and output mechanisms for a Quantum Secure Email Client Application is paramount to ensuring both robust security and a user-friendly experience. It must seamlessly integrate the complexities of quantum-resistant cryptography with intuitive user interfaces.

Input Design: Empowering Secure Composition

The input design needs to accommodate standard email functionalities while incorporating secure cryptographic practices:

1. Email Content (Enhanced):

- **Rich Text Support:** Beyond plain text and HTML, consider supporting rich text formatting options (bold, italics, underlining, lists, etc.) that are securely rendered without introducing vulnerabilities.
- **Attachment Handling with Security Focus:** When attaching files, the system should provide clear visual cues about their encryption status. Options for individually encrypting attachments with different keys or access controls could be valuable for granular security.
- **Draft Saving with Encryption:** Even email drafts could be stored in an encrypted format locally to prevent unauthorized access.
- **Metadata Considerations:** Allow users to specify metadata (e.g., priority, sensitivity level) that could influence the encryption protocols or access controls applied.

2. Recipient Information (Secure Management):

- **Quantum-Secure Contact Management:** The contact list itself should be stored using quantum-resistant encryption. Consider features like securely associating public keys with contacts.
- **Key Verification:** Mechanisms for users to verify the authenticity and integrity of recipients' public keys are crucial. This could involve visual indicators, fingerprint comparisons, or integration with a secure key server.
- **Group Encryption:** Facilitate secure communication with multiple recipients through group encryption schemes that are quantum-resistant.

- **Revocation Handling:** Allow senders to revoke access to previously sent encrypted emails if necessary (though this is a complex feature with implications for key management).
3. **Encryption Key (Advanced Management):**
- **Quantum-Resistant Algorithm Selection:** Provide users with a clear choice of quantum-resistant encryption algorithms (e.g., lattice-based cryptography, code-based cryptography, multivariate cryptography, hash-based signatures). Offer guidance on the strengths and weaknesses of each.
 - **Key Generation Options:** Offer secure, locally generated key pair options. Consider integration with Quantum Key Distribution (QKD) mechanisms if the infrastructure allows, providing the highest level of security.
 - **Key Storage:** Implement secure local storage of private keys, potentially leveraging hardware security modules (HSMs) or secure enclaves for enhanced protection.
 - **Key Exchange Protocols:** For initial secure communication, the application needs robust quantum-resistant key exchange protocols. Make this process transparent but secure for the user.
 - **Key Backup and Recovery:** Provide secure mechanisms for users to back up and recover their private keys in case of device loss or failure. This needs to be balanced with security to prevent unauthorized recovery.
4. **Authentication Credentials (Quantum-Proofing):**
- **Strong Password Policies:** Enforce robust password complexity requirements.
 - **Multi-Factor Authentication (MFA):** Strongly emphasize and support various MFA methods, including time-based one-time passwords (TOTP), biometric authentication, and potentially even quantum-resistant authentication factors in the future.
 - **Secure Credential Storage:** Store authentication credentials using strong, quantum-resistant hashing algorithms or encryption.
 - **Session Management:** Implement secure session management to prevent unauthorized access after successful authentication.
5. **Configuration Settings (Granular Control):**
- **Per-Email Encryption Settings:** Allow users to customize encryption algorithms and key usage on a per-email basis for different levels of security.

- **Default Encryption Preferences:** Enable users to set default encryption algorithms and key preferences for outgoing emails.
- **Key Management Policies:** Allow users to define policies for key rotation, expiration, and storage.
- **Security Level Indicators:** Provide clear visual indicators of the current security level applied to an email being composed.
- **Notification Preferences (Security-Focused):** Allow users to customize alerts for key changes, potential security breaches, or suspicious activity.

Output Design: Ensuring Secure Delivery and Access

The output design focuses on delivering encrypted content securely and providing necessary feedback to users:

1. Encrypted Email Messages (Quantum-Secured):

- **Algorithm Tagging:** Encrypted emails should clearly indicate the quantum-resistant encryption algorithm used for transparency and compatibility.
- **Integrity Protection:** Ensure that the encryption process includes mechanisms to verify the integrity of the message during transmission and upon decryption.
- **Metadata Encryption (Optional):** Consider options to encrypt email metadata (e.g., subject line, sender/recipient information) for enhanced privacy.

2. Encrypted Attachments (Confidentiality Guaranteed):

- **Separate Encryption:** Clearly indicate if attachments are encrypted separately from the email body and the algorithm used.
- **Access Control for Attachments:** Explore the possibility of implementing granular access controls for attachments, allowing the sender to specify which recipients can access specific files.

3. Secure Transmission Protocols (Future-Proofing):

- **TLS/SSL Enhancement:** Investigate and implement quantum-resistant key exchange mechanisms within TLS/SSL or explore next-generation secure transport protocols that are inherently quantum-secure.
- **S/MIME with Quantum Resistance:** Adapt or develop S/MIME protocols that utilize quantum-resistant cryptographic algorithms for end-to-end encryption and digital signatures.

- **Decentralized Transmission:** Explore decentralized or peer-to-peer email transmission methods that could offer enhanced security and resilience against quantum attacks on central servers.
4. **Encryption Key Management (User-Centric Security):**
- **Key Status Indicators:** Provide users with clear visual indicators of the status and validity of their encryption keys and the recipients' keys.
 - **Key Exchange Notifications:** Notify users when new keys are exchanged or when key updates occur.
 - **Secure Key Sharing Mechanisms:** Implement secure methods for users to share their public keys with new contacts, potentially using out-of-band verification.
 - **Key Revocation Management:** Provide a clear and secure process for users to revoke compromised keys and notify their contacts.
5. **Message Status and Delivery Confirmation (Secure Tracking):**
- **Encrypted Delivery Receipts:** Explore the possibility of end-to-end encrypted delivery and read receipts to maintain confidentiality.
 - **Tamper Detection:** Implement mechanisms to detect if an encrypted email has been tampered with during transmission.
 - **Security Alerting:** Provide timely alerts about potential security threats, such as attempts to decrypt messages with invalid keys or suspicious network activity.
6. **User Interface Feedback (Security Awareness):**
- **Clear Encryption Status:** Prominently display the encryption status of composed, sent, and received emails.
 - **Security Level Visualizations:** Use visual cues (e.g., color-coding, icons) to indicate the strength of the encryption used.
 - **Informative Error Messages:** Provide clear and helpful error messages related to encryption and decryption failures, guiding users on how to resolve issues.
 - **Security Best Practice Tips:** Offer contextual tips and guidance on secure email practices within the user interface.
7. **Decryption and Viewing Tools (Authorized Access Only):**
- **Seamless Decryption:** The decryption process for authorized recipients should be as seamless as possible, ideally happening automatically upon opening the email.

- **Key Validation:** The decryption tool must securely validate the recipient's private key against the encryption parameters of the received email.
- **Secure Rendering:** Ensure that decrypted content, especially HTML, is rendered securely to prevent the execution of malicious scripts.
- **Attachment Decryption:** Provide a secure and intuitive way for recipients to decrypt and access encrypted attachments.
- **Audit Trails (Optional):** For high-security environments, consider implementing audit trails of decryption activities.

By meticulously designing both the input and output aspects of a Quantum Secure Email Client Application with a strong focus on user experience and the intricacies of quantum-resistant cryptography, you can empower users to communicate securely in the face of future quantum computing capabilities. The key is to balance robust security with usability, ensuring that users can easily adopt and effectively utilize these advanced security measures.

CHAPTER – 6: SOFTWARE ENVIRONMENT

What is Python :

Below are some facts about Python.

Python is currently the most widely used multi-purpose, high-level programming language. Python allows programming in Object-Oriented and Procedural paradigms. Python programs generally are smaller than other programming languages like Java. Programmers have to type relatively less and indentation requirement of the language, makes them readable all the time.

Python language is being used by almost all tech-giant companies like – Google, Amazon, Facebook, Instagram, Dropbox, Uber... etc.

The biggest strength of Python is huge collection of standard library which can be used for the following – • Machine Learning

- GUI Applications (like Kivy, Tkinter, PyQtetc.)
- Web frameworks like Django (used by YouTube, Instagram, Dropbox)
- Image processing (like Opencv, Pillow)
- Web scraping (like Scrappy, BeautifulSoup, Selenium)
- Test frameworks
- Multimedia
-

Advantages of Python :-

Let's see how Python dominates over other languages.

1. Extensive Libraries

Python downloads with an extensive library and it contain code for various purposes like regular expressions, documentation-generation, unit-testing, web browsers, threading, databases, CGI, email, image manipulation, and more. So, we don't have to write the complete code for that manually.

2. Extensible

As we have seen earlier, Python can be extended to other languages. You can write some of your code in languages like C++ or C. This comes in handy, especially in projects.

3. Embeddable

Complimentary to extensibility, Python is embeddable as well. You can put your Python code in your source code of a different language, like C++. This lets us add **scripting capabilities** to our code in the other language.

4. Improved Productivity

The language's simplicity and extensive libraries render programmers **more productive** than languages like Java and C++ do. Also, the fact that you need to write less and get more things done.

5. IOT Opportunities

Since Python forms the basis of new platforms like Raspberry Pi, it finds the future bright for the Internet Of Things. This is a way to connect the language with the real world.

When working with Java, you may have to create a class to print '**Hello World**'. But in Python, just a print statement will do. It is also quite **easy to learn, understand, and code**. This is why when people pick up Python, they have a hard time adjusting to other more verbose languages like Java.

7. Readable

Because it is not such a verbose language, reading Python is much like reading English. This is the reason why it is so easy to learn, understand, and code. It also does not need curly braces to define blocks, and **indentation is mandatory**. This further aids the readability of the code.

8. Object-Oriented

This language supports both the **procedural and object-oriented** programming paradigms. While functions help us with code reusability, classes and objects let us model the real world. A class allows the **encapsulation of data** and functions into one.

9. Free and Open-Source

Like we said earlier, Python is **freely available**. But not only can you **download Python** for free, but you can also download its source code, make changes to it, and even distribute it. It downloads with an extensive collection of libraries to help you with your tasks.

10. Portable

When you code your project in a language like C++, you may need to make some changes to it if you want to run it on another platform. But it isn't the same with Python. Here, you need to **code only once**, and you can run it anywhere.

This is called **Write Once Run Anywhere (WORA)**. However, you need to be careful enough not to include any system-dependent features.

11. Interpreted

Lastly, we will say that it is an interpreted language. Since statements are executed one by one, **debugging is easier** than in compiled languages.

Any doubts till now in the advantages of Python? Mention in the comment section.

Advantages of Python Over Other Languages :

1. Less Coding

Almost all of the tasks done in Python requires less coding when the same task is done in other languages. Python also has an awesome standard library support, so you don't have to search for any third-party libraries to get your job done. This is the reason that many people suggest learning Python to beginners.

2. Affordable

Python is free therefore individuals, small companies or big organizations can leverage the free available resources to build applications. Python is popular and widely used so it gives you better community support.

The 2019 Github annual survey showed us that Python has overtaken Java in the most popular programming language category.

3. Python is for Everyone

Python code can run on any machine whether it is Linux, Mac or Windows. Programmers need to learn different languages for different jobs but with Python, you can professionally build web apps, perform data analysis and **machine learning**, automate things, do web scraping and also build games and powerful visualizations. It is an all-rounder programming language

Disadvantages of Python

So far, we've seen why Python is a great choice for your project. But if you choose it, you should be aware of its consequences as well. Let's now see the downsides of choosing Python over another language.

1. Speed Limitations

We have seen that Python code is executed line by line. But since Python is interpreted, it often results in **slow execution**. This, however, isn't a problem unless speed is a focal point for the project. In other words, unless high speed is a requirement, the benefits offered by Python are enough to distract us from its speed limitations.

2. Weak in Mobile Computing and Browsers

While it serves as an excellent server-side language, Python is much rarely seen on the **client-side**. Besides that, it is rarely ever used to implement smartphone-based applications. One such application is called **Carbonnelle**.

The reason it is not so famous despite the existence of Brython is that it isn't that secure.

3. Design Restrictions

As you know, Python is **dynamically-typed**. This means that you don't need to declare the type of variable while writing the code. It uses **duck-typing**. But wait, what's that? Well, it just means that if it looks like a duck, it must be a duck. While this is easy on the programmers during coding, it can **raise run-time errors**.

4. Underdeveloped Database Access Layers

Compared to more widely used technologies like **JDBC (Java DataBase Connectivity)** and **ODBC (Open DataBase Connectivity)**, Python's database access layers are a bit underdeveloped. Consequently, it is less often applied in huge enterprises.

5. Simple

No, we're not kidding. Python's simplicity can indeed be a problem. Take my example. I don't do Java, I'm more of a Python person. To me, its syntax is so simple that the verbosity of Java code seems unnecessary.

This was all about the Advantages and Disadvantages of Python Programming Language.

History of Python :-

What do the alphabet and the programming language Python have in common? Right, both start with ABC. If we are talking about ABC in the Python context, it's clear that the programming language ABC is meant. ABC is a general-purpose programming language and programming environment, which had been developed in the Netherlands, Amsterdam,

at the CWI (Centrum Wiskunde&Informatica). The greatest achievement of ABC was to influence the design of Python. Python was conceptualized in the late 1980s. Guido van Rossum worked that time in a project at the CWI, called Amoeba, a distributed operating system. In an interview with Bill Venners¹, Guido van Rossum said: "In the early 1980s, I worked as an implementer on a team building a language called ABC at Centrum voor Wiskunde en Informatica (CWI). I don't know how well people know ABC's influence on Python. I try to mention ABC's influence because I'm indebted to everything I learned during that project and to the people who worked on it." Later on in the same interview, Guido van Rossum continued:

"I remembered all my experience and some of my frustration with ABC. I decided to try to design a simple scripting language that possessed some of ABC's better properties, but without its problems. So I started typing. I created a simple virtual machine, a simple parser, and a simple runtime. I made my own version of the various ABC parts that I liked. I created a basic syntax, used indentation for statement grouping instead of curly braces or begin-end blocks, and developed a small number of powerful data types: a hash table (or dictionary, as we call it), a list, strings, and numbers."

What is Machine Learning : -

Before we take a look at the details of various machine learning methods, let's start by looking at what machine learning is, and what it isn't. Machine learning is often categorized as a subfield of artificial intelligence, but I find that categorization can often be misleading at first brush. The study of machine learning certainly arose from research in this context, but in the data science application of machine learning methods, it's more helpful to think of machine learning as a means of building models of data.

Fundamentally, machine learning involves building mathematical models to help understand data. "Learning" enters the fray when we give these models tunable parameters that can be adapted to observed data; in this way the program can be considered to be "learning" from the data. Once these models have been fit to previously seen data, they can be used to predict and understand aspects of newly observed data. I'll leave to the reader the more philosophical digression regarding the extent to which this type of mathematical, model-based "learning" is similar to the "learning" exhibited by the human brain. Understanding the problem setting in machine learning is essential to using these tools effectively, and so we will start with some broad categorizations of the types of approaches we'll discuss here.

Categories Of Machine Learning :-

At the most fundamental level, machine learning can be categorized into two main types: supervised learning and unsupervised learning.

Supervised learning involves somehow modeling the relationship between measured features of data and some label associated with the data; once this model is determined, it can be used to apply labels to new, unknown data.

This is further subdivided into classification tasks and regression tasks: in classification, the labels are discrete categories, while in regression, the labels are continuous quantities. We will see examples of both types of supervised learning in the following section.

Unsupervised learning involves modeling the features of a dataset without reference to any label, and is often described as "letting the dataset speak for itself." These models include tasks such as clustering and dimensionality reduction. Clustering algorithms identify distinct groups of data, while dimensionality reduction algorithms search for more succinct representations of the data. We will see examples of both types of unsupervised learning in the following section.

Need for Machine Learning

Human beings, at this moment, are the most intelligent and advanced species on earth because they can think, evaluate and solve complex problems. On the other side, AI is still in its initial stage and haven't surpassed human intelligence in many aspects. Then the question is that what is the need to make machine learn? The most suitable reason for doing this is, "to make decisions, based on data, with efficiency and scale".

Lately, organizations are investing heavily in newer technologies like Artificial Intelligence, Machine Learning and Deep Learning to get the key information from data to perform several real-world tasks and solve problems. We can call it data-driven decisions taken by machines, particularly to automate the process. These data-driven decisions can be used, instead of using programming logic, in the problems that cannot be programmed inherently. The fact is that we can't do without human intelligence, but other aspect is that we all need to solve realworld problems with efficiency at a huge scale. That is why the need for machine learning arises.

Challenges in Machines Learning :-

While Machine Learning is rapidly evolving, making significant strides with cybersecurity and autonomous cars, this segment of AI as whole still has a long way to go. The reason behind is that ML has not been able to overcome number of challenges. The challenges that ML is facing currently are –

Quality of data – Having good-quality data for ML algorithms is one of the biggest challenges. Use of low-quality data leads to the problems related to data preprocessing and feature extraction.

Time-Consuming task – Another challenge faced by ML models is the consumption of time especially for data acquisition, feature extraction and retrieval.

Lack of specialist persons – As ML technology is still in its infancy stage, availability of expert resources is a tough job.

No clear objective for formulating business problems – Having no clear objective and well-defined goal for business problems is another key challenge for ML because this technology is not that mature yet.

Issue of overfitting & underfitting – If the model is overfitting or underfitting, it cannot be represented well for the problem.

Curse of dimensionality – Another challenge ML model faces is too many features of data points. This can be a real hindrance.

Difficulty in deployment – Complexity of the ML model makes it quite difficult to be deployed in real life.

Applications of Machines Learning :-

Machine Learning is the most rapidly growing technology and according to researchers we are in the golden year of AI and ML. It is used to solve many real-world complex problems which cannot be solved with traditional approach. Following are some real-world applications of ML –

- Emotion analysis
- Sentiment analysis
- Error detection and prevention
- Weather forecasting and prediction
- Stock market analysis and forecasting
- Speech synthesis
- Speech recognition
- Customer segmentation
- Object recognition
- Fraud detection
- Fraud prevention

. Recommendation of products to customer in online shopping

. How to Start Learning Machine Learning?

Arthur Samuel coined the term “**Machine Learning**” in 1959 and defined it as a “**Field of study that gives computers the capability to learn without being explicitly programmed**”.

And that was the beginning of Machine Learning! In modern times, Machine Learning is one of the most popular (if not the most!) career choices. According to Indeed, Machine Learning Engineer Is The Best Job of 2019 with a 344% growth and an average base salary of \$146,085 per year.

But there is still a lot of doubt about what exactly is Machine Learning and how to start learning it? So this project deals with the Basics of Machine Learning and also the path you can follow to eventually become a full-fledged Machine Learning Engineer. Now let's get started!!!

How to start learning ML?

This is a rough roadmap you can follow on your way to becoming an insanely talented Machine Learning Engineer. Of course, you can always modify the steps according to your needs to reach your desired end-goal! **Step 1 – Understand the Prerequisites**

In case you are a genius, you could start ML directly but normally, there are some prerequisites that you need to know which include Linear Algebra, Multivariate Calculus, Statistics, and Python. And if you don't know these, never fear! You don't need a Ph.D. degree in these topics to get started but you do need a basic understanding.

(a) Learn Linear Algebra and Multivariate Calculus

Both Linear Algebra and Multivariate Calculus are important in Machine Learning. However, the extent to which you need them depends on your role as a data scientist. If you are more focused on application heavy machine learning, then you will not be that heavily focused on maths as there are many common libraries available. But if you want to focus on R&D in Machine Learning, then mastery of Linear Algebra and Multivariate

Calculus is very important as you will have to implement many ML algorithms from scratch.

(b) Learn Statistics

Data plays a huge role in Machine Learning. In fact, around 80% of your time as an ML expert will be spent collecting and cleaning data. And statistics is a field that handles the collection, analysis, and presentation of data. So it is no surprise that you need to learn it!!! Some of the key concepts in statistics that are important are Statistical Significance, Probability Distributions, Hypothesis Testing, Regression, etc. Also, Bayesian Thinking is also a very important part of ML which deals with various concepts like Conditional Probability, Priors, and Posteriors, Maximum Likelihood, etc.

(c) Learn Python

Some people prefer to skip Linear Algebra, Multivariate Calculus and Statistics and learn them as they go along with trial and error. But the one thing that you absolutely cannot skip is Python!

While there are other languages you can use for Machine Learning like R, Scala, etc. Python is currently the most popular language for ML. In fact, there are many Python libraries that are specifically useful for Artificial Intelligence and Machine Learning such as Keras, TensorFlow, Scikit-learn, etc.

So if you want to learn ML, it's best if you learn Python! You can do that using various online resources and courses such as **Fork Python** available Free on GeeksforGeeks.

Step 2 – Learn Various ML Concepts

Now that you are done with the prerequisites, you can move on to actually learning ML (Which is the fun part!!!) It's best to start with the basics and then move on to the more complicated stuff. Some of the basic concepts in ML are:

(a) Terminologies of Machine Learning

- **Model** – A model is a specific representation learned from data by applying some machine learning algorithm. A model is also called a hypothesis.
- **Feature** – A feature is an individual measurable property of the data. A set of numeric features can be conveniently described by a feature vector. Feature vectors are fed as input to the model. For example, in order to predict a fruit, there may be features like color, smell, taste, etc.
- **Target (Label)** – A target variable or label is the value to be predicted by our model. For the fruit example discussed in the feature section, the label with each set of input would be the name of the fruit like apple, orange, banana, etc.
- **Training** – The idea is to give a set of inputs(features) and it's expected outputs(labels), so after training, we will have a model (hypothesis) that will then map new data to one of the categories trained on.
- **Prediction** – Once our model is ready, it can be fed a set of inputs to which it will provide a predicted output(label).

(b) Types of Machine Learning

- **Supervised Learning** – This involves learning from a training dataset with labeled data using classification and regression models. This learning process continues until the required level of performance is achieved.

- **Unsupervised Learning** – This involves using unlabelled data and then finding the underlying structure in the data in order to learn more and more about the data itself using factor and cluster analysis models.
- **Semi-supervised Learning** – This involves using unlabelled data like Unsupervised Learning with a small amount of labeled data. Using labeled data vastly increases the learning accuracy and is also more cost-effective than Supervised Learning.
- **Reinforcement Learning** – This involves learning optimal actions through trial and error. So the next action is decided by learning behaviors that are based on the current state and that will maximize the reward in the future.

Advantages of Machine learning :- 1. Easily identifies trends and patterns -

Machine Learning can review large volumes of data and discover specific trends and patterns that would not be apparent to humans. For instance, for an e-commerce website like Amazon, it serves to understand the browsing behaviors and purchase histories of its users to help cater to the right products, deals, and reminders relevant to them. It uses the results to reveal relevant advertisements to them.

1. No human intervention needed (automation)

With ML, you don't need to babysit your project every step of the way. Since it means giving machines the ability to learn, it lets them make predictions and also improve the algorithms on their own. A common example of this is anti-virus softwares; they learn to filter new threats as they are recognized. ML is also good at recognizing spam.

2. Continuous Improvement

As **ML algorithms** gain experience, they keep improving in accuracy and efficiency. This lets them make better decisions. Say you need to make a weather forecast model. As the amount of data you have keeps growing, your algorithms learn to make more accurate predictions faster.

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5. Handling multi-dimensional and multi-variety data

Machine Learning algorithms are good at handling data that are multi-dimensional and multivariety, and they can do this in dynamic or uncertain environments.

6. Wide Applications

You could be an e-tailer or a healthcare provider and make ML work for you. Where it does apply, it holds the capability to help deliver a much more personal experience to customers while also targeting the right customers.

Disadvantages of Machine Learning :- 1. Data Acquisition

Machine Learning requires massive data sets to train on, and these should be inclusive/unbiased, and of good quality. There can also be times where they must wait for new data to be generated.

2. Time and Resources

ML needs enough time to let the algorithms learn and develop enough to fulfill their purpose with a considerable amount of accuracy and relevancy. It also needs massive resources to function. This can mean additional requirements of computer power for you.

3. Interpretation of Results

Another major challenge is the ability to accurately interpret results generated by the algorithms. You must also carefully choose the algorithms for your purpose.

4. High error-susceptibility

Machine Learning is autonomous but highly susceptible to errors. Suppose you train an algorithm with data sets small enough to not be inclusive. You end up with biased predictions coming from a biased training set. This leads to irrelevant advertisements being displayed to customers. In the case of ML, such blunders can set off a chain of errors that can go undetected for long periods of time. And when they do get noticed, it takes quite some time to recognize the source of the issue, and even longer to correct it.

Python Development Steps :-

Guido Van Rossum published the first version of Python code (version 0.9.0) at alt.sources in February 1991. This release included already exception handling, functions, and the core data types of list, dict, str and others. It was also object oriented and had a module system. Python version 1.0 was released in January 1994. The major new features included in this release were the functional programming tools lambda, map, filter and reduce, which Guido Van Rossum never liked. Six and a half years later in October 2000, Python 2.0 was introduced. This release included list comprehensions, a full garbage collector and it was supporting unicode. Python flourished for another 8 years in the versions 2.x before the next major release as Python

3.0 (also known as "Python 3000" and "Py3K") was released. Python 3 is not backwards compatible with Python 2.x. The emphasis in Python 3 had been on the removal of duplicate programming constructs and modules, thus fulfilling or coming close to fulfilling the 13th law of the Zen of Python: "There should be one -- and preferably only one -- obvious way to do it." Some changes in Python 3:

- Print is now a function
- Views and iterators instead of lists
- The rules for ordering comparisons have been simplified. E.g. a heterogeneous list cannot be sorted, because all the elements of a list must be comparable to each other.
- There is only one integer type left, i.e. int. long is int as well.

- The division of two integers returns a float instead of an integer. "/" can be used to have the "old" behaviour.
- Text Vs. Data Instead Of Unicode Vs. 8-bit

Purpose :-

We demonstrated that our approach enables successful segmentation of intra-retinal layers—even with low-quality images containing speckle noise, low contrast, and different intensity ranges throughout—with the assistance of the ANIS feature.

Python

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace. Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

- Python is Interpreted – Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- Python is Interactive – you can actually sit at a Python prompt and interact with the interpreter directly to write your programs.

Python also acknowledges that speed of development is important. Readable and terse code is part of this, and so is access to powerful constructs that avoid tedious repetition of code. Maintainability also ties into this may be an all but useless metric, but it does say something about how much code you have to scan, read and/or understand to troubleshoot problems or tweak behaviors. This speed of development, the ease with which a programmer of other languages can pick up basic Python skills and the huge standard library is key to another area where Python excels. All its tools have been quick to implement, saved a lot of time, and several of them have later been patched and updated by people with no Python background - without breaking.

Modules Used in Project :- Tensorflow

TensorFlow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks. It is used for both research and production at Google.

TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache 2.0 open-source license on November 9, 2015.

Numpy

Numpy is a general-purpose array-processing package. It provides a high- performance multidimensional array object, and tools for working with these arrays.

It is the fundamental package for scientific computing with Python. It contains various features including these important ones:

- A powerful N-dimensional array object
- Sophisticated (broadcasting) functions
- Tools for integrating C/C++ and Fortran code
- Useful linear algebra, Fourier transform, and random number capabilities Besides its obvious scientific uses, Numpy can also be used as an efficient multidimensional container of generic data. Arbitrary data-types can be defined using Numpy which allows Numpy to seamlessly and speedily integrate with a wide variety of databases.

Pandas

Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. Python was majorly used for data munging and preparation. It had very little contribution towards data analysis. Pandas solved this problem. Using Pandas, we can accomplish five typical steps in the processing and analysis of data, regardless of the origin of data load, prepare, manipulate, model, and analyze. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

Matplotlib

Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms.

Matplotlib can be used in Python scripts, the Python and IPython shells, the Jupyter Notebook, web application servers, and four graphical user interface toolkits. Matplotlib tries to make easy things easy and hard things possible. You can generate plots, histograms, power spectra, bar charts, error charts, scatter plots, etc., with just a few lines of code. For examples, see the sample plots and thumbnail gallery.

For simple plotting the pyplot module provides a MATLAB-like interface, particularly when combined with IPython. For the power user, you have full control of line styles, font properties, axes properties, etc, via an object oriented interface or via a set of functions familiar to MATLAB users.

Scikit – learn

Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python. It is licensed under a permissive simplified BSD license and is distributed under many Linux distributions, encouraging academic and commercial use.

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Install Python Step-by-Step in Windows and Mac :

Python a versatile programming language doesn't come pre-installed on your computer devices. Python was first released in the year 1991 and until today it is a very popular high-level programming language. Its style philosophy emphasizes code readability with its notable use of great whitespace.

The object-oriented approach and language construct provided by Python enables programmers to write both clear and logical code for projects. This software does not come pre-packaged with Windows.

How to Install Python on Windows and Mac :

There have been several updates in the Python version over the years. The question is how to install Python? It might be confusing for the beginner who is willing to start learning Python but this tutorial will solve your query. The latest or the newest version of Python is version 3.7.4 or in other words, it is Python 3.

Note: The python version 3.7.4 cannot be used on Windows XP or earlier devices.

Before you start with the installation process of Python. First, you need to know about your **System Requirements**. Based on your system type i.e. operating system and based processor, you must download the python version. My system type is a **Windows 64-bit operating system**. So the steps below are to install python version 3.7.4 on Windows 7 device or to install Python 3. Download the Python Cheatsheet [here](#). The steps on how to install Python on Windows 10, 8 and 7 are **divided into 4 parts** to help understand better.

Download the Correct version into the system

Step 1: Go to the official site to download and install python using Google Chrome or any other web browser. OR Click on the following link: <https://www.python.org>



Now, check for the latest and the correct version for your operating system.

Step 2: Click on the Download Tab.



Step 3: You can either select the Download Python for windows 3.7.4 button in Yellow Color or you can scroll further down and click on

download with respective to their version. Here, we are downloading the most recent python version for windows 3.7.4

Looking for a specific release?

Python releases by version number:

Release version	Release date		Click for more
Python 3.7.4	July 8, 2019	Download	Release Notes
Python 3.6.9	July 2, 2019	Download	Release Notes
Python 3.7.3	March 25, 2019	Download	Release Notes
Python 3.4.10	March 18, 2019	Download	Release Notes
Python 3.5.7	March 18, 2019	Download	Release Notes
Python 2.7.18	March 4, 2019	Download	Release Notes
Python 3.7.2	Dec. 24, 2018	Download	Release Notes

Step 4: Scroll down the page until you find the Files option.

Step 5: Here you see a different version of python along with the operating system.

Files

Version	Operating System	Description	MD5 Sum	File Size	GP0
Unipped source tarball	Source release		68111671e5b3db4e7f6b6b10f099be	23817663	565
GZ compressed source tarball	Source release		033e44ae6027051c3b645ee364803	17131432	565
macOS 64-bit/32-bit installer	Mac OS X	for Mac OS X 10.6 and later	6428b4fa7933baf1a44c3a3ce08e6	34898436	565
macOS 64-bit installer	Mac OS X	for OS X 10.9 and later	5dd070c30217e4f733bfe4e938d41f	20082845	565
Windows help file	Windows		063090573a2c56b2ac3acadeb047c02	8131761	565
Windows x86-64 embeddable zip file	Windows	for AMD64/EM64T/x64	5b2073d5faffec0baf6e3184a41728a2	7564391	565
Windows x86-64 executable installer	Windows	for AMD64/EM64T/x64	a703b4bca076d9d030c3a563e543400	2688348	565
Windows x86-64 web-based installer	Windows	for AMD64/EM64T/x64	28c31c0288d73a9e53a3a3f351b4bd2	1362904	565
Windows x86 embeddable zip file	Windows		9fab38d138b438799da94133574139d3	6741628	565
Windows x86 executable installer	Windows		31c3002942a5446a3d5e451470394789	25663848	565
Windows x86 web-based installer	Windows		1b670cfa0d217dfe3c3086ba371a87c	1324008	565

- To download Windows 32-bit python, you can select any one from the three options: Windows x86 embeddable zip file, Windows x86 executable installer or Windows x86 webbased installer.

- To download Windows 64-bit python, you can select any one from the three options: Windows x86-64 embeddable zip file, Windows x86-64 executable installer or Windows x8664 web-based installer.

Here we will install Windows x86-64 web-based installer. Here your first part regarding which version of python is to be downloaded is completed.

Now we move ahead with the second part in installing python i.e. Installation

Note: To know the changes or updates that are made in the version you can click on the Release Note Option.

Installation of Python

Step 1: Go to Download and Open the downloaded python version to carry out the installation process.



Step 2: Before you click on Install Now, Make sure to put a tick on Add Python 3.7 to PATH.



Step 3: Click on Install NOW After the installation is successful. Click on Close.

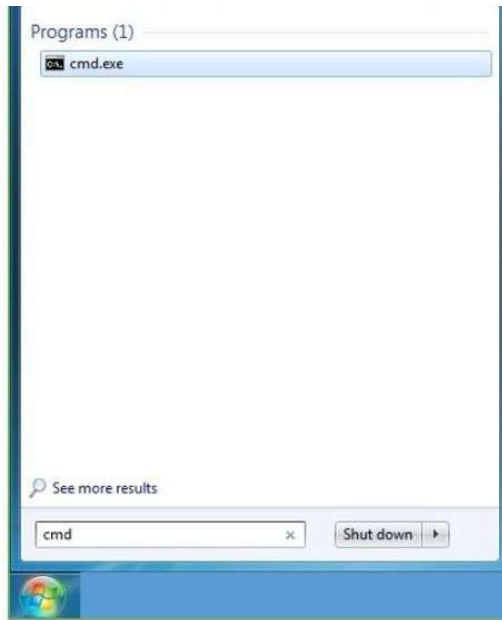


With these above three steps on python installation, you have successfully and correctly installed Python. Now is the time to verify the installation.

Note: The installation process might take a couple of minutes.

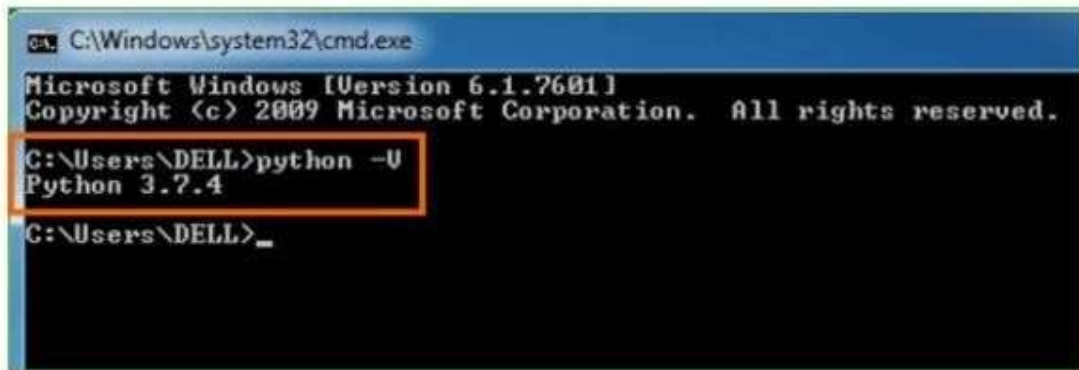
Verify the Python Installation Step 1: Click on Start

Step 2: In the Windows Run Command, type “cmd”.



Step 3: Open the Command prompt option.

Step 4: Let us test whether the python is correctly installed. Type **python -V** and press Enter.

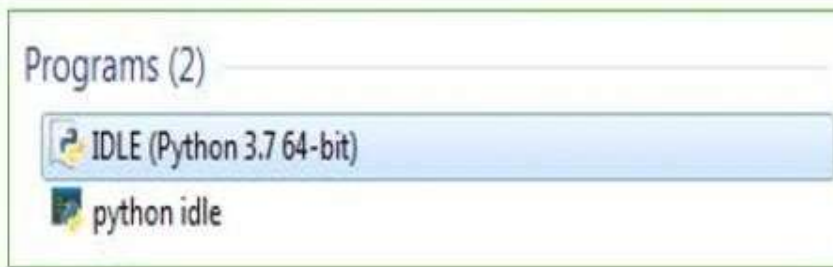


Step 5: You will get the answer as 3.7.4

Note: If you have any of the earlier versions of Python already installed. You must first uninstall the earlier version and then install the new one.

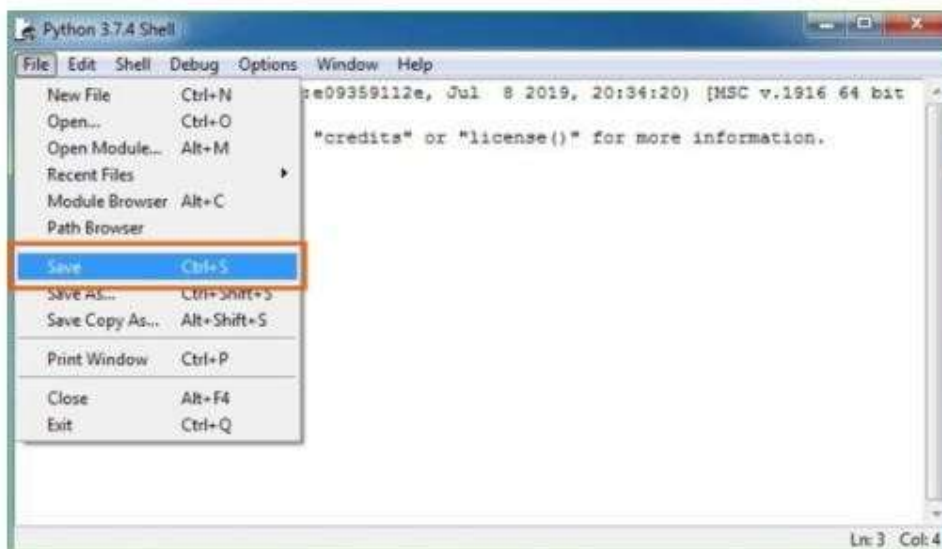
Check how the Python IDLE works Step 1: Click on Start

Step 2: In the Windows Run command, type “python idle”.



Step 3: Click on IDLE (Python 3.7 64-bit) and launch the program

Step 4: To go ahead with working in IDLE you must first save the file. **Click on File > Click on Save**



Step 5: Name the file and save as type should be Python files. Click on SAVE. Here I have named the files as Hey World.

Step 6: Now for e.g. **enter print**

CHAPTER-VII SYSTEM TESTING

SYSTEM TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub assemblies, assemblies and/or a finished product. It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

TYPES OF TESTS

Unit testing :

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application. It is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

Integration testing

Integration tests are designed to test integrated software components to determine if they actually run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfactory, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

Functional test

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

Valid Input : identified classes of valid input must be accepted. Invalid Input
: identified classes of invalid input must be rejected. Functions
: identified functions must be exercised.

Output : identified classes of application outputs must be exercised.

Systems/Procedures : interfacing systems or procedures must be invoked.

Organization and preparation of functional tests is focused on requirements, key functions, or special test cases. In addition, systematic coverage pertaining to identify Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before functional testing is complete, additional tests are identified and the effective value of current tests is determined.

System Test

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

White Box Testing

White Box Testing is a testing in which the software tester has knowledge of the inner workings, structure and language of the software, or at least its purpose.

It is purpose. It is used to test areas that cannot be reached from a black box level.

Black Box Testing

Black Box Testing is testing the software without any knowledge of the inner workings, structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements document, such as specification or requirements document. It is a testing in which the software under test is treated, as a black box .you cannot “see” into it. The test provides inputs and responds to outputs without considering how the software works.

Unit Testing

Unit testing is usually conducted as part of a combined code and unit test phase of the software lifecycle, although it is not uncommon for coding and unit testing to be conducted as two distinct phases.

Test strategy and approach

Field testing will be performed manually and functional tests will be written in detail.

Test objectives

- All field entries must work properly.
- Pages must be activated from the identified link.
- The entry screen, messages and responses must not be delayed.

Features to be tested

- Verify that the entries are of the correct format
- No duplicate entries should be allowed
- All links should take the user to the correct page.

Integration Testing

Software integration testing is the incremental integration testing of two or more integrated software components on a single platform to produce failures caused by interface defects.

The task of the integration test is to check that components or software applications, e.g. components in a software system or – one step up – software applications at the company level – interact without error.

Test Results:All the test cases mentioned above passed successfully. No defects encountered.

Acceptance Testing

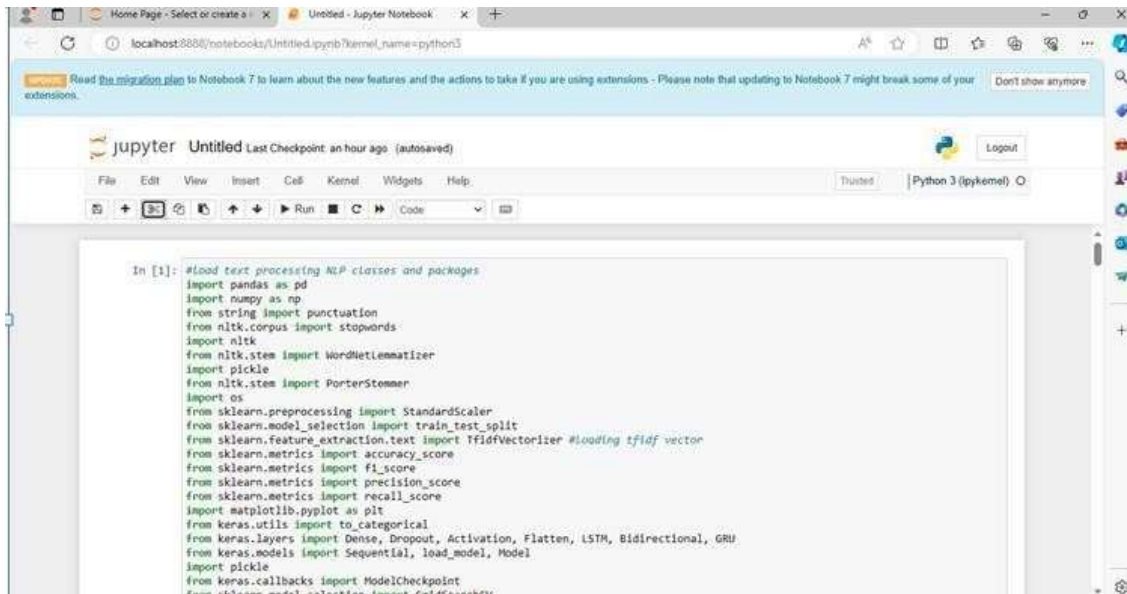
User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

Test Results:All the test cases mentioned above passed successfully. No defects encountered.

CHAPTER-VIII

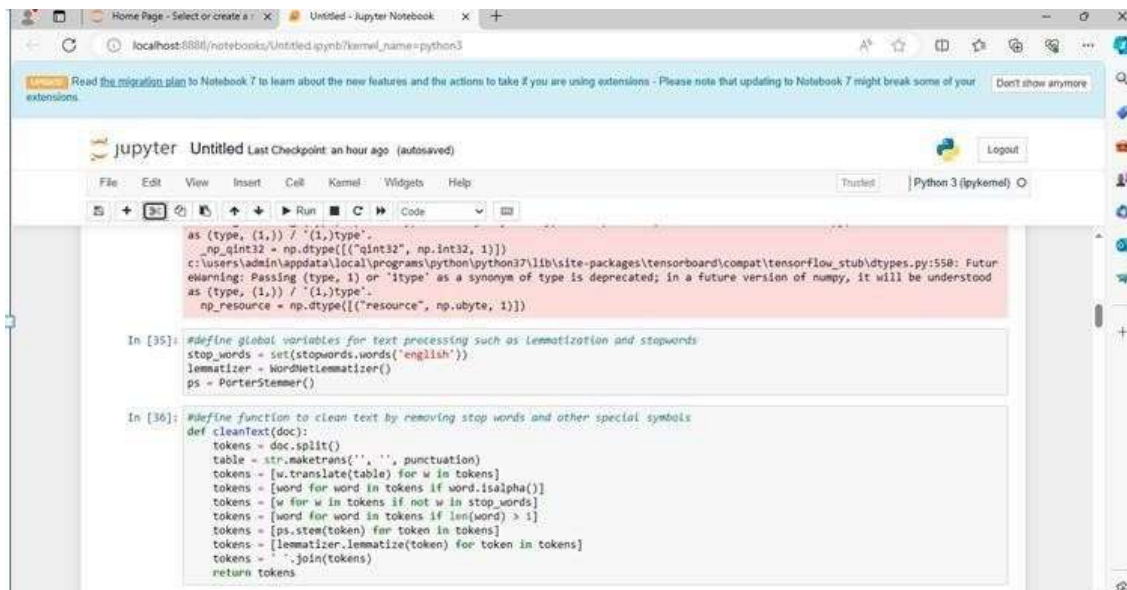
SCREENSHOTS

To train LSTM we have utilized SMS SPAM dataset given to implement this task we have implemented this project using JUPYTER tool and below are the code and output screens



```
In [1]: #Load text processing NLP classes and packages
import pandas as pd
import numpy as np
from string import punctuation
from nltk.corpus import stopwords
import nltk
from nltk.stem import WordNetLemmatizer
import pickle
from nltk.stem import PorterStemmer
import os
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer #Loading tfidf vector
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
import matplotlib.pyplot as plt
from keras.utils import to_categorical
from keras.layers import Dense, Dropout, Activation, Flatten, LSTM, Bidirectional, GRU
from keras.models import Sequential, load_model, Model
import pickle
from keras.callbacks import ModelCheckpoint
from sklearn.model_selection import GridSearchCV
```

Above screen shots showing loading of required classes and packages

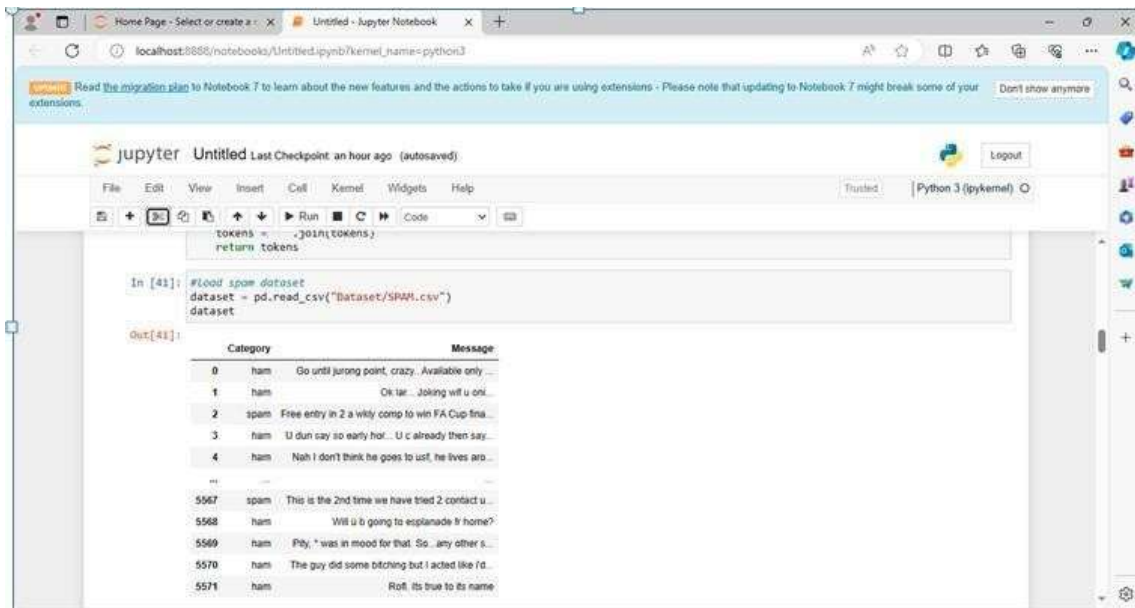


```
as (type, (1,)) / '(1,)type'.
np_int32 = np.dtype([('int32', np.int32, 1)])
c:\users\admin\appdata\local\programs\python\python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:558: Future
warning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood
as (type, (1,)) / '(1,)type'.
np_resource = np.dtype([('resource', np.ubyte, 1)])

In [35]: #define global variables for text processing such as lemmatization and stopwords
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()
ps = PorterStemmer()

In [36]: #define function to clean text by removing stop words and other special symbols
def cleanText(doc):
    tokens = doc.split()
    table = str.maketrans('', '', punctuation)
    tokens = [w.translate(table) for w in tokens]
    tokens = [word for word in tokens if word.isalpha()]
    tokens = [w for w in tokens if not w in stop_words]
    tokens = [word for word in tokens if len(word) > 1]
    tokens = [ps.stem(token) for token in tokens]
    tokens = [lemmatizer.lemmatize(token) for token in tokens]
    tokens = ' '.join(tokens)
    return tokens
```

in above page we have utilized classes from NLTK package to remove stop words, stemming and lemmatization and in above screen cleaning text message with this classes



The screenshot shows a Jupyter Notebook interface with a code cell and its output. The code cell contains the following Python code:

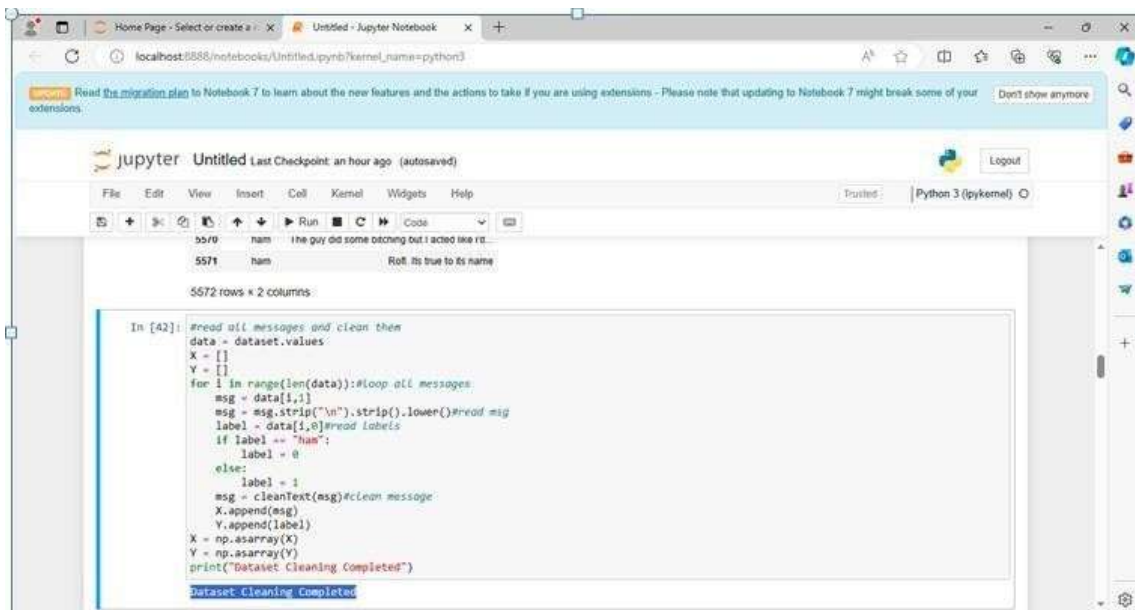
```
tokens = ' '.join(tokens)
return tokens

In [41]: #load spam dataset
dataset = pd.read_csv("dataset/SPAM.csv")
dataset
```

The output of the code cell is a table with two columns: 'Category' and 'Message'. The table contains 5571 rows of data, including ham and spam messages.

	Category	Message
0	ham	Go until jurong point, crazy. Available only
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup final
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives ar...
...
5567	spam	This is the 2nd time we have tried 2 contact u...
5568	ham	Will u b going to esplanade fr home?
5569	ham	Ply, "was in mood for that. So... any other s...
5570	ham	The guy did some bitching but I acted like I'd...
5571	ham	Rofl. Its true to its name

In above screen loading and displaying dataset values.



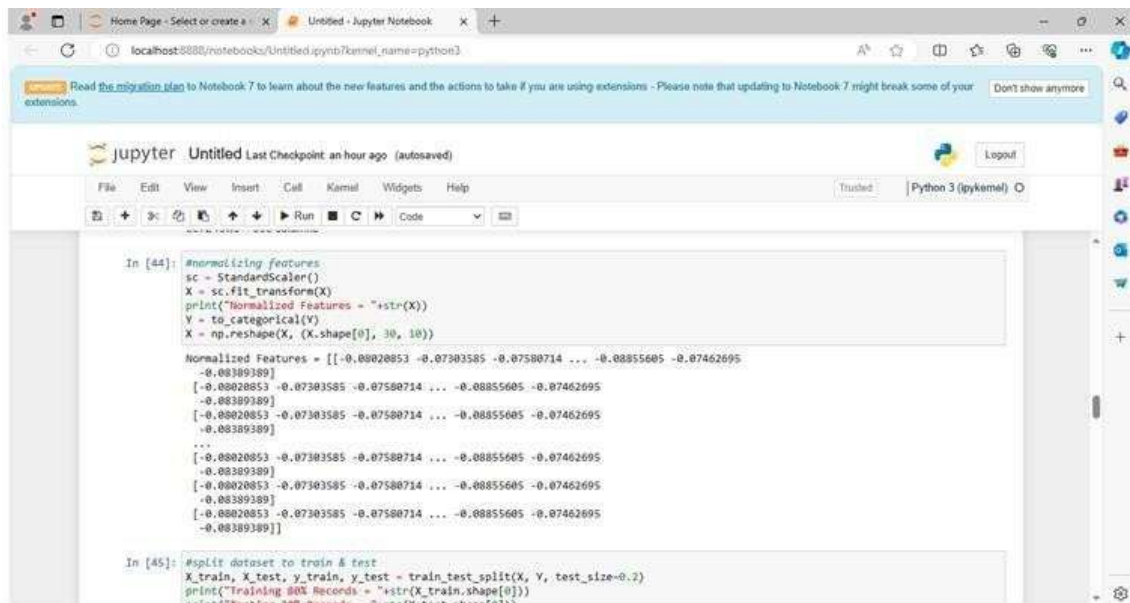
The screenshot shows a Jupyter Notebook interface with a code cell and its output. The code cell contains the following Python code:

```
5570 ham the guy did some bitching but I acted like ra
5571 ham Rofl. Its true to its name

5572 rows x 2 columns

In [42]: #read all messages and clean them
data = dataset.values
X = []
Y = []
for i in range(len(data)): #loop all messages
    msg = data[i,1]
    msg = msg.strip("\n").strip().lower() #read msg
    label = data[i,0] #read labels
    if label == "ham":
        label = 0
    else:
        label = 1
    msg = cleanText(msg) #clean message
    X.append(msg)
    Y.append(label)
X = np.asarray(X)
Y = np.asarray(Y)
print("Dataset Cleaning Completed")
Dataset Cleaning Completed
```

In above screen looping all messages and then calling CLEAN function to remove stop words, stemming and lemmatization will be applied and then create X and Y training array.

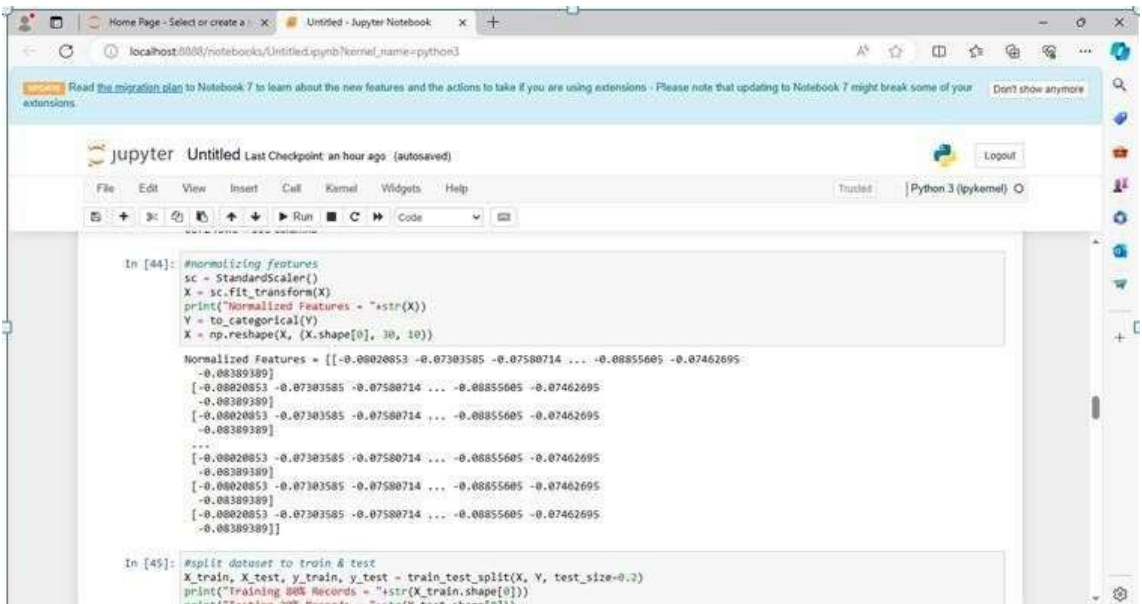


```
In [44]: #normalizing features
sc = StandardScaler()
X = sc.fit_transform(X)
print("Normalized Features = "+str(X))
Y = to_categorical(Y)
X = np.reshape(X, (X.shape[0], 30, 10))

Normalized Features = [[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]
[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]
[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]
...
[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]
[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]
[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]]

In [45]: #split dataset to train & test
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)
print("Training 80% Records = "+str(X_train.shape[0]))
print("Testline 20% Records = "+str(X_test.shape[0]))
```

n above screen using vector class we have converted all text into fixed size numeric vector and in above vector all column contains word NAMES and remaining rows contains average occurrence of that column words



```
In [44]: #normalizing features
sc = StandardScaler()
X = sc.fit_transform(X)
print("Normalized Features = "+str(X))
Y = to_categorical(Y)
X = np.reshape(X, (X.shape[0], 30, 10))

Normalized Features = [[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]
[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]
[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]
...
[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]
[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]
[-0.00020053 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695
-0.00309309]]

In [45]: #split dataset to train & test
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)
print("Training 80% Records = "+str(X_train.shape[0]))
print("Testline 20% Records = "+str(X_test.shape[0]))
```

In above screen normalizing entire numeric vector and then displaying normalize values

The screenshot shows a Jupyter Notebook interface with the following code and output:

```
X = np.reshape(X, (X.shape[0], 30, 10))
```

Normalized Features =

```
[[-0.00020853 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695  
 -0.00389389]  
 [-0.00020853 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695  
 -0.00389389]  
 [-0.00020853 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695  
 -0.00389389]  
 ...  
 [-0.00020853 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695  
 -0.00389389]  
 [-0.00020853 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695  
 -0.00389389]  
 [-0.00020853 -0.07303585 -0.07500714 ... -0.00855605 -0.07462695  
 -0.00389389]]
```

```
In [45]: #split dataset to train & test  
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)  
print("Training 80% Records = "+str(X_train.shape[0]))  
print("Testing 20% Records = "+str(X_test.shape[0]))
```

Training 80% Records = 4497
Testing 20% Records = 1115

```
In [46]: #define LSTM algorithm  
lstm_model = Sequential()#defining deep learning sequential object
```

In above page splitting dataset into train and test where application using 80% dataset messages for training and 20% for testing.

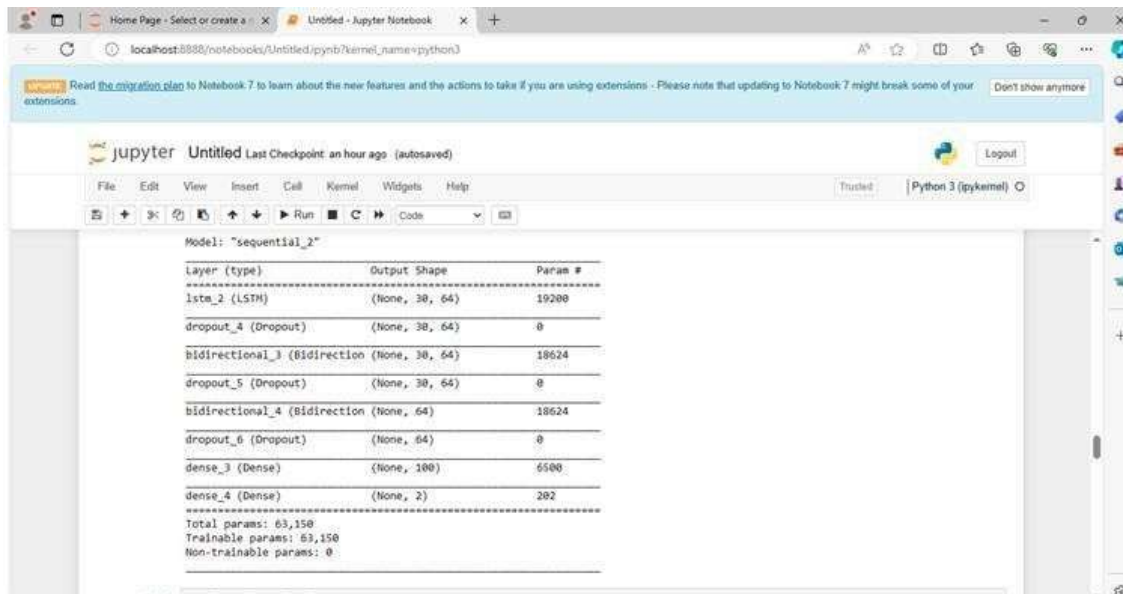
The screenshot shows a Jupyter Notebook interface with the following code and output:

```
Testing 20% Records = 1115
```

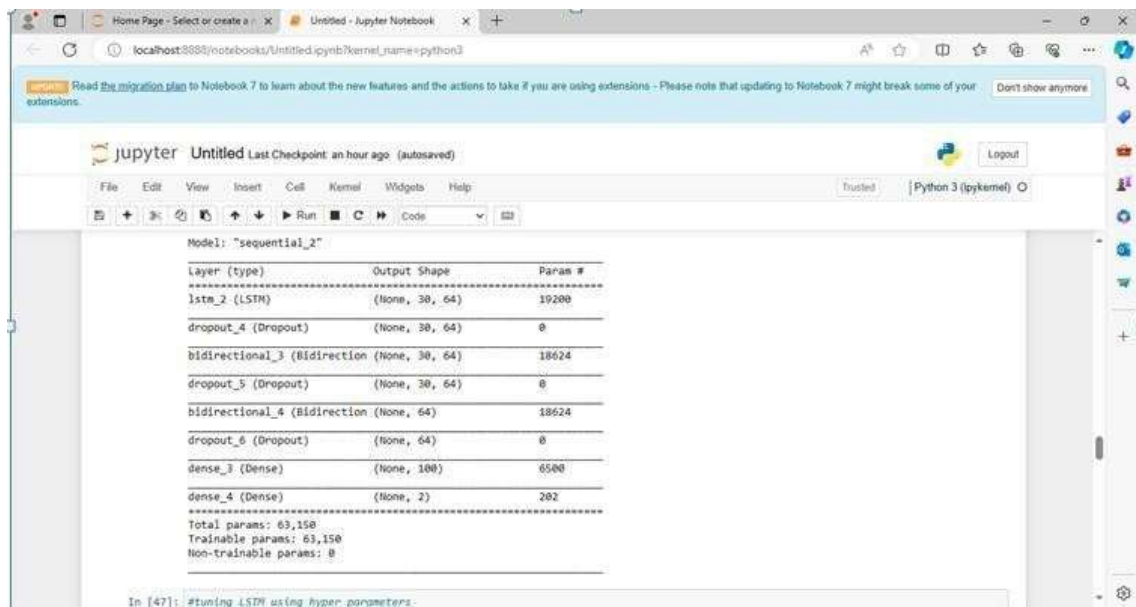
```
In [46]: #define LSTM algorithm  
lstm_model = Sequential()#defining deep learning sequential object  
#adding LSTM layer with 100 filters to filter given input X train data to select relevant features  
lstm_model.add(LSTM(64, input_shape=(X_train.shape[1], X_train.shape[2]), return_sequences=True))  
lstm_model.add(Dropout(0.5))  
lstm_model.add(Bidirectional(GRU(32, return_sequences=True)))  
#adding dropout layer to remove irrelevant features  
lstm_model.add(Dropout(0.5))  
lstm_model.add(Bidirectional(GRU(32)))  
lstm_model.add(Dropout(0.5))  
#adding another layer  
lstm_model.add(Dense(100, activation='relu'))  
#defining output layer for prediction  
lstm_model.add(Dense(y_train.shape[1], activation='softmax'))  
#compile the model  
lstm_model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['accuracy'])  
lstm_model.summary()
```

Model: "sequential_2"

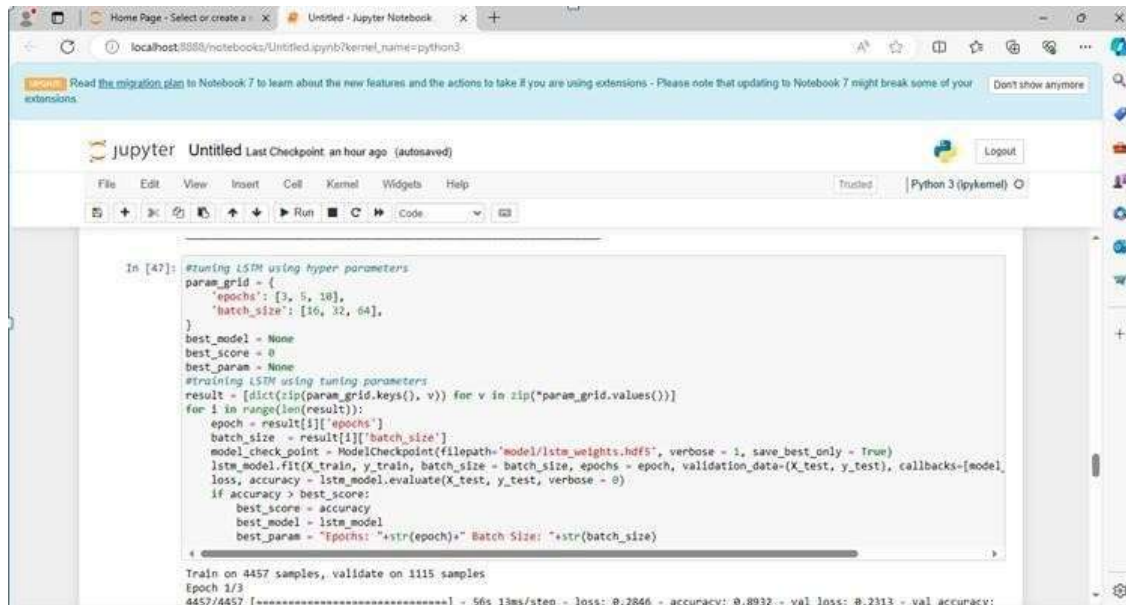
Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 30, 64)	19200



In above screen defining LSTM architecture and below is the summary of above model.



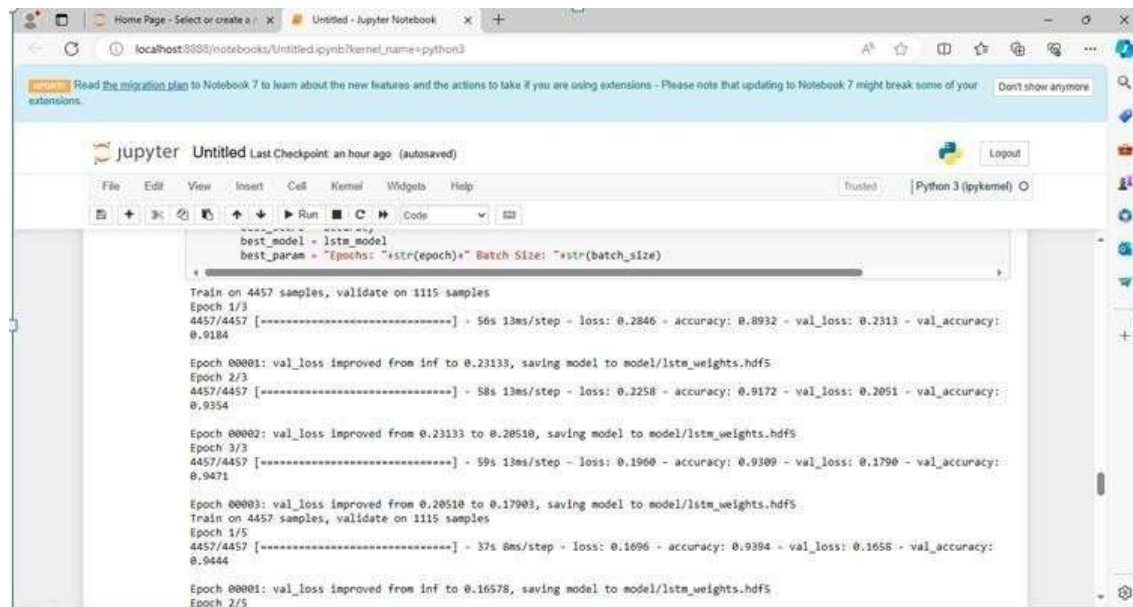
In above screen can see LSTM model summary.



```
In [47]: #tuning LSTM using hyper parameters
param_grid = {
    'epochs': [3, 5, 10],
    'batch_size': [16, 32, 64],
}
best_model = None
best_score = 0
best_param = None
#training LSTM using tuning parameters
result = [dict(zip(param_grid.keys(), v)) for v in zip(*param_grid.values())]
for i in range(len(result)):
    epoch = result[i]['epochs']
    batch_size = result[i]['batch_size']
    model_checkpoint = ModelCheckpoint(filepath="model/lstm_weights.hdf5", verbose = 1, save_best_only = True)
    lstm_model.fit(X_train, y_train, batch_size = batch_size, epochs = epoch, validation_data=(X_test, y_test), callbacks=[model_checkpoint])
    loss, accuracy = lstm_model.evaluate(X_test, y_test, verbose = 0)
    if accuracy > best_score:
        best_score = accuracy
        best_model = lstm_model
        best_param = "Epochs: "+str(epoch)+" Batch Size: "+str(batch_size)
```

Train on 4457 samples, validate on 1115 samples
Epoch 1/3
4457/4457 [=====] - 56s 13ms/step - loss: 0.2846 - accuracy: 0.8932 - val_loss: 0.2313 - val accuracy:

In above screen training LSTM model by employing tuning parameters and while training will get below output.



```
best_model = lstm_model
best_param = "Epochs: "+str(epoch)+" Batch Size: "+str(batch_size)
```

Train on 4457 samples, validate on 1115 samples
Epoch 1/3
4457/4457 [=====] - 56s 13ms/step - loss: 0.2846 - accuracy: 0.8932 - val_loss: 0.2313 - val_accuracy: 0.9184
Epoch 00001: val_loss improved from inf to 0.23133, saving model to model/lstm_weights.hdf5
Epoch 2/3
4457/4457 [=====] - 58s 13ms/step - loss: 0.2258 - accuracy: 0.9172 - val_loss: 0.2051 - val_accuracy: 0.9354
Epoch 00002: val_loss improved from 0.23133 to 0.20510, saving model to model/lstm_weights.hdf5
Epoch 3/3
4457/4457 [=====] - 59s 13ms/step - loss: 0.1960 - accuracy: 0.9309 - val_loss: 0.1790 - val_accuracy: 0.9471
Epoch 00003: val_loss improved from 0.20510 to 0.17903, saving model to model/lstm_weights.hdf5
Train on 4457 samples, validate on 1115 samples
Epoch 1/5
4457/4457 [=====] - 37s 8ms/step - loss: 0.1696 - accuracy: 0.9394 - val_loss: 0.1658 - val_accuracy: 0.9444
Epoch 00001: val_loss improved from inf to 0.16578, saving model to model/lstm_weights.hdf5
Epoch 2/5

In above screen LSTM starts training as per tuning parameters and after all parameters will get below best score and parameters values.

The screenshot shows a Jupyter Notebook interface with the following content:

```

Epoch 00009: val_loss did not improve from 0.15144
Epoch 10/10
4457/4457 [=====] - 21s 56s/step - loss: 0.0949 - accuracy: 0.9695 - val_loss: 0.1725 - val_accuracy:
0.9525

Epoch 00010: val_loss did not improve from 0.15144

In [48]: print("Best Score: "+str(best_score))
         print("Best Tuning Params: "+str(best_param))

Best Score: 0.9524663686752319
Best Tuning Params: Epochs: 10 Batch Size: 64

In [50]: #evaluating best model performance
predict = best_model.predict(X_test)
predict = np.argmax(predict, axis=1)
y_test1 = np.argmax(y_test, axis=1)
a = accuracy_score(y_test1, predict)*100
p = precision_score(y_test1, predict,average='macro') * 100
r = recall_score(y_test1, predict,average='macro') * 100
f = f1_score(y_test1, predict,average='macro') * 100
print("Best Model Performance Measure")
print("Accuracy: "+str(a))
print("Precision: "+str(p))
print("Recall: "+str(r))

```

In above screen can see best model score and tuning parameters and now we are performing prediction on test data using BEST MODEL.

The screenshot shows a Jupyter Notebook interface with the following content:

```

print("Best Tuning Params: "+str(best_param))

Best Score: 0.9524663686752319
Best Tuning Params: Epochs: 10 Batch Size: 64

In [50]: #evaluating best model performance
predict = best_model.predict(X_test)#performing prediction on test data using best model
predict = np.argmax(predict, axis=1)
y_test1 = np.argmax(y_test, axis=1)
a = accuracy_score(y_test1, predict)*100 #calculate accuracy and other metrics using original labels and predicted labels
p = precision_score(y_test1, predict,average='macro') * 100
r = recall_score(y_test1, predict,average='macro') * 100
f = f1_score(y_test1, predict,average='macro') * 100
print("Best Model Performance Measure")
print("Accuracy: "+str(a))
print("Precision: "+str(p))
print("Recall: "+str(r))
print("FSORE: "+str(f))

Best Model Performance Measure
Accuracy: 95.24663677138846
Precision: 91.82831776594726
Recall: 86.67269006928645
FSORE: 89.08811764248874

```

In above page in blue colour text can see accuracy, precision, recall and FCSORE of best model predicted on unknown 20% test data and this model able to classify SPAM messages with an accuracy of over 98%.

CHAPTER-IX CONCLUSION

CONCLUSION

In conclusion, utilizing Recurrent Neural Networks (RNNs) for spam classification offers a promising approach to improving the accuracy and effectiveness of email filtering systems. RNNs, and specifically Long Short-Term Memory (LSTM) networks, are well-suited for this task due to their ability to capture long-range dependencies in sequential data, which is crucial for understanding the context of an email. By leveraging the power of deep learning, RNNs can automatically learn relevant features from email data, reducing the need for manual feature engineering and potentially improving performance. Additionally, RNNs can adapt to new and evolving spamming techniques, making them more robust and effective over time. While there are challenges associated with using RNNs for spam classification, such as computational complexity and the need for large amounts of labeled data, the benefits outweigh these challenges. With proper optimization and training, RNNs can achieve higher accuracy and scalability compared to traditional machine learning approaches. Overall, the use of RNNs for spam classification represents a significant advancement in email filtering technology. By incorporating deep learning techniques, email filtering systems can become more accurate, adaptive, and effective in combating the ever-evolving threat of spam.

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