A Major Project Report

on

SMS SPAM DETECTION USING MACHINE LEARNING TECHNIQUES

Submitted in partial fulfillment of the Requirements for the award of degree of

Bachelor of Engineering

in

Computer Science and Engineering

by

T.SAI TEJA **2203A52123**

Under the guidance of

Dr. M. Sreenivasulu

Professor

Department of CSE

CERTIFICATE

This is to Certify that A Project report entitled **"SMS Spam Detection using Machine Learning Techniques**" is being submitted by T SaiTeja (2203A52123)**,** in partial fulfilment of the requirement of the award for the degree of Bachelor of Engineering in "Computer Science and Engineering" during the year 2024-2025 is a record of work carried out by him/her under my guidance. The results presented in this thesis have been verified and are found to be satisfactory.

External Examiner(s)

Department of Computer Science and Engineering

DECLARATION

I **Mr. Saiteja** bearing **H.T.No. 2203a52123** hereby certify that the project report entitled **“SMS Spam Detection Using Machine Learning Techniques”** is submitted in the partial fulfilment of the requirement for the award of the degree of **Bachelor of Engineering** in **Computer Science and Engineering.**

This is a record of the bonafide work carried out by us under the guidance. The Results embodied in this report have not been reproduced/copied from any source. The results embodied in this report have not been submitted to any other University or Institute for the award of any other degree or diploma.

T.SAI TEJA 2203A52123

Dept. of CSE, MECS

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ABSTRACT

Machine learning and artificial intelligence applications are in wide spread. They are making the human world an error free and easy. The number of people using mobile devices increasing day by day. SMS (short message service) is a text message service available in smartphones as well as basic phones. So, the traffic of SMS increased drastically. The spam messages also increased. The hackers try to send spam messages for their financial or business benefits like market growth, lottery ticket information, credit card information, etc. So, spam classification has special attention. The applications of Machine Learning (ML) and Artificial Intelligence (AI) have become increasingly widespread, offering powerful solutions that enhance accuracy and simplify human tasks. With the growing number of mobile phone users globally, the usage of SMS (Short Message Service) has seen a significant surge. Alongside this increase, there has been a parallel rise in spam messages unsolicited or fraudulent messages that often aim to promote fake lotteries, credit card offers, or other financial scams. These spam messages not only clutter communication but can also pose serious security risks To address this challenge, our project presents a comprehensive approach to SMS spam detection by leveraging both machine learning and deep learning models.

We trained and evaluated multiple models: Naive Bayes (NB), Support Vector Machine (SVM), Random Forest (RF), and a deep learning model based on Long Short-Term Memory (LSTM) networks. The SMS Spam Collection dataset was used to train and test the performance of these models. This dataset was preprocessed using Natural Language

Processing (NLP) techniques and split into training and testing sets for evaluation. Naive Bayes, SVM, and Random Forest were trained using TF-IDF features, enabling them to effectively classify messages based on keyword patterns. Among the traditional ML models, the Naive Bayes classifier demonstrated particularly strong performance with high accuracy and minimal computational cost. In parallel, we implemented an LSTM model an advanced type of Recurrent Neural Network (RNN) which excels in processing sequential data like text by capturing long-term dependencies and contextual meaning within messages. Our results show that while traditional machine learning models like NB, SVM, and RF perform well, the LSTM model offers superior performance in terms of understanding the semantics and context of cleverly disguised spam.

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CHAPTER 1

INTRODUCTION

In today's technology-driven world, mobile communication plays an essential role in daily life, supporting personal, social, and commercial exchanges. Among the available communication methods, Short Message Service (SMS) remains one of the most accessible and widely used due to its simplicity, low cost, and compatibility across all types of mobile devices. However, this widespread use of SMS has also made it a common target for exploitation through spam messages. These spam messages often carry promotional content, phishing links, or deceptive schemes that aim to compromise user privacy or financial security.

The rise of SMS spam poses a growing concern for both users and mobile service providers. Traditional spam filters such as keyword-based detection or static blacklists have proven to be limited and often ineffective against evolving spamming techniques. Spammers continuously modify the structure and content of their messages to bypass such simple rulebased filters. As a result, there is a pressing need for more intelligent, adaptive, and robust spam detection mechanisms.

To address this challenge, our project applies a combination of Machine Learning (ML) and Deep Learning (DL) techniques to automatically detect and filter SMS spam. Specifically, we have trained and evaluated four different models: Naive Bayes, Support Vector Machine (SVM), Random Forest, and Long Short-Term Memory (LSTM) networks. These models are capable of learning from labeled historical SMS data and making accurate predictions on whether a new message is spam or not (ham).

The project uses the well-established SMS Spam Collection Dataset, which contains thousands of real-world SMS messages labeled as spam or ham. This dataset enables comprehensive training and evaluation of the models in realistic conditions. For traditional ML models like Naive Bayes, SVM, and Random Forest, we employed text vectorization using TF-IDF (Term Frequency-Inverse Document Frequency) to extract numerical features from messages. For the LSTM model, we used tokenization and sequence padding to process text into a format suitable for deep learning.

One of the major challenges in SMS spam detection is the unstructured and informal nature of SMS messages. These texts are often brief, include slang or abbreviations, and vary significantly in vocabulary and syntax. To overcome these challenges, our project integrates Natural Language Processing (NLP) techniques to clean and preprocess the text before feeding it into the models.

The primary objective of this project is to develop a high-performing, scalable spam detection system that can be integrated into mobile applications or messaging platforms. By combining the strengths of both classical ML and modern DL approaches, we aim to provide a solution that is not only accurate but also adaptable to new and sophisticated spam tactics. Our experimental results show that all models performed effectively, with Naive Bayes offering quick and reliable classification, and LSTM providing deeper contextual understanding of messages for improved accuracy.

In conclusion, this project highlights the potential of machine learning and deep learning in enhancing digital communication security. By identifying and filtering spam messages proactively, such systems can reduce user annoyance, prevent fraud, and improve overall user experience. This work also serves as a practical demonstration of how intelligent models can be applied to real-world problems using standard ML workflows data preprocessing, feature extraction, model training, evaluation, and deployment.

CHAPTER 2 LITERATURE SURVEY

The problem of spam detection has been a long-standing challenge in the field of natural language processing and information security. With the proliferation of SMS-based communication, there has been a significant shift in research interest towards developing efficient models for filtering out spam messages. Early research in spam detection was largely driven by rule-based and keyword-matching systems, which used manually crafted heuristics to identify suspicious content. While such approaches were easy to implement, they were rigid and prone to failure in the face of evolving spam patterns. These limitations necessitated the use of more intelligent and adaptable techniques, which led to the application of machine learning and, more recently, deep learning methods.

One of the earliest and most influential works in SMS spam detection was by Almeida et al. (2011), who developed the SMS Spam Collection Dataset, a widely used benchmark comprising over 5,000 messages labeled as "ham" or "spam." Their study demonstrated the applicability of basic machine learning algorithms such as Naive Bayes, Support Vector Machines (SVM), and Decision Trees for text classification tasks. These models relied heavily on feature engineering, particularly the use of Bag-of-Words (BoW) and TF-IDF representations to convert text into numerical vectors. Despite their simplicity, these techniques yielded reasonably good performance, establishing a baseline for future work.

Following this, several researchers explored the use of ensemble methods and advanced feature selection techniques to improve accuracy. Islam et al. (2013) proposed a model combining SVM with a feature selection method based on chi-square statistics. Their system achieved higher precision in identifying spam messages by focusing on statistically significant words and phrases. Similarly, Bhattacharyya et al. (2015) incorporated natural language processing techniques to extract semantic and syntactic features from SMS texts. However, these traditional machine learning methods had inherent limitations: they depended heavily on manual feature engineering, which was not only time-consuming but also required domain expertise.

To address these limitations, recent studies have turned to deep learning, particularly models capable of capturing sequential and contextual relationships in text. One of the most influential classes of deep learning models for text processing is the Recurrent Neural Network (RNN). RNNs are designed to work with sequential data, making them well-suited for understanding the order and context of words in SMS messages. However, traditional RNNs suffer from the vanishing gradient problem, which makes it difficult to capture longterm dependencies in text.

This issue was mitigated by the introduction of Long Short-Term Memory (LSTM) networks, a special type of RNN proposed by Hochreiter and Schmidhuber in 1997. LSTM networks are equipped with memory cells and gating mechanisms that allow them to retain information over long sequences, making them highly effective in modeling the contextual flow of language. In the context of spam detection, LSTMs offer the ability to learn patterns that span across multiple words, which is particularly useful in identifying deceptive or disguised spam messages that might escape traditional filters.

Several recent studies have demonstrated the effectiveness of LSTM networks for spam detection tasks. Zhang et al. (2018) proposed an SMS spam detection model using a bidirectional LSTM (Bi-LSTM) network. Their model was able to capture both past and future word contexts, improving the semantic understanding of each message. They reported significantly higher accuracy compared to conventional ML models, especially in identifying spam messages with subtle phrasing. Similarly, Kadhim (2019) implemented an LSTM-based spam classifier that used word embeddings such as Word2Vec and GloVe to represent SMS content. These embeddings helped in capturing the semantic similarity between words, enabling the model to generalize better across varied spam formats.

Other researchers have experimented with hybrid deep learning models, combining LSTM layers with Convolutional Neural Networks (CNNs) or attention mechanisms. For instance, a study by Mishra and Bhattacharyya (2020) integrated CNNs with LSTMs to capture both local and sequential features from SMS text. Their architecture benefited from CNNs' ability to detect key n-gram patterns and LSTM's capability to understand the sequence of these patterns. The model achieved excellent performance in benchmark datasets, underlining the power of hybrid approaches in spam detection.

In addition to model architecture, preprocessing and data representation have been critical components of successful spam detection systems. While early ML models relied on simple frequency-based representations, deep learning models have advanced to using embedding layers that transform words into dense vector spaces. Embedding techniques such as Word2Vec, GloVe, and FastText have been extensively used in spam detection research.

These embeddings not only reduce dimensionality but also encode syntactic and semantic relationships between words, improving model performance.

A growing body of literature also explores transfer learning and the use of large pretrained language models like BERT (Bidirectional Encoder Representations from Transformers) for spam detection. Though not directly focused on SMS spam, these models have shown promise in similar text classification tasks, and there is ongoing research to adapt them to short message formats. Nonetheless, LSTM remains a preferred choice for SMS spam classification due to its efficiency, ease of training on small to medium datasets, and strong ability to model sequential text.

In conclusion, the evolution of spam detection has mirrored the broader trends in machine learning and natural language processing. While traditional ML models laid the groundwork for automatic classification systems, they have largely been outperformed by deep learning approaches, particularly LSTM networks. The literature consistently demonstrates that LSTMs offer superior performance in capturing contextual nuances in SMS messages, making them well-suited for the spam detection task. The integration of LSTM with modern NLP tools such as word embeddings, bidirectional networks, and hybrid deep learning architectures has further enhanced detection accuracy and robustness. This body of work provides a strong foundation for our project, which aims to implement an LSTM-based SMS spam detection system capable of handling real-world messaging data with high precision and recall. Over the years, SMS spam detection has evolved from basic rule-based filters to more advanced machine learning and deep learning approaches. Early models, such as Naive Bayes and SVM, relied heavily on manual feature extraction using techniques like Bag-ofWords and TF-IDF. While effective to some extent, these models struggled with understanding context and evolving spam patterns. Recent advancements in deep learning, particularly the use of Long Short-Term Memory (LSTM) networks, have significantly improved spam detection by capturing the sequential nature and contextual dependencies of text. Studies show that LSTM-based models, especially when combined with word embeddings, outperform traditional methods in both accuracy and robustness, making them a powerful choice for SMS spam classification.

Researchers have also explored enhancements to LSTM models by integrating techniques like bidirectional LSTMs (Bi-LSTM), which process text in both forward and backward directions to gain a better understanding of word context. Some studies have combined LSTM with Convolutional Neural Networks (CNNs) to capture both local and sequential features, improving the model’s ability to detect complex spam patterns. Furthermore, the use of pre-trained word embeddings such as Word2Vec and GloVe has allowed models to better represent the semantic meaning of words, enhancing their ability to distinguish spam from legitimate messages. These innovations have established LSTM-based architectures as a reliable and efficient solution in the ongoing effort to combat SMS spam.

CHAPTER – 3 SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Traditional spam detection systems are primarily based on classical machine learning algorithms such as Naive Bayes, Decision Trees, and Logistic Regression. These models depend heavily on manually engineered features like word frequency (term frequency), bagof-words representations, or the presence of specific keywords. Such systems typically classify messages based on static rule sets or shallow statistical patterns, which may work well for identifying straightforward spam content. However, they face significant challenges when dealing with modern and more complex spam strategies. Spammers often use techniques like intentional misspellings (e.g., "Fr33" instead of "Free"), symbol replacements, or altering word order to bypass keyword filters. Additionally, these models fail to capture the semantic meaning or contextual relationships between words, leading to decreased accuracy when spam messages resemble genuine content or evolve over time. Because of their limited flexibility and inability to understand language context, these systems are not well-suited for handling the dynamic and deceptive nature of current spam messages. As a result, they often produce high false positives and fail to detect cleverly crafted spam, reducing the effectiveness of the spam filtering mechanism.

3.2 PROPOSED SYSTEM

The proposed system is designed to accurately detect SMS spam messages using both traditional machine learning algorithms and advanced deep learning techniques. Unlike rulebased methods that rely on predefined keywords, this system adopts a data-driven approach capable of learning patterns from historical SMS data. It aims to classify messages as either *spam* or *ham* (non-spam) by training and evaluating four models: Naive Bayes, Support Vector Machine (SVM), Random Forest, and Long Short-Term Memory (LSTM) networks. This hybrid model selection provides flexibility and allows a comparative analysis of different algorithmic approaches for text classification.

The foundation of this system is the SMS Spam Collection Dataset, which consists of thousands of real-world SMS messages labelled as spam or ham. The dataset undergoes preprocessing steps such as lowercasing, removal of stopwords, punctuation handling, and tokenization to ensure that the models receive clean and meaningful input. For traditional machine learning models like Naive Bayes, SVM, and Random Forest, the system uses TFIDF (Term Frequency-Inverse Document Frequency) to convert the raw text into numerical feature vectors that reflect the importance of each word relative to the entire corpus.

Naive Bayes is chosen for its simplicity and efficiency in text classification tasks, especially where features are independent. SVM is used because of its ability to handle highdimensional spaces and provide clear decision boundaries between spam and ham. Random Forest adds the benefit of ensemble learning by combining the predictions of multiple decision trees, thus improving generalization and reducing overfitting. These models are effective for straightforward spam detection but are limited in understanding the order and contextual flow of words within a message.

To overcome the limitations of traditional models, the system incorporates LSTM, a variant of Recurrent Neural Networks (RNNs), which excels at modeling sequential data. LSTM networks use memory cells and gating mechanisms to retain relevant information over time, allowing them to understand the context of words in a sentence. This is especially important in detecting cleverly disguised spam messages that do not contain obvious spam keywords but rely on sentence structure and semantics to deceive users.

For the LSTM model, the SMS messages are preprocessed using tokenization and sequence padding so that they can be fed into the network in a format it can learn from. Unlike TFIDF, which loses the order of words, LSTM captures the sequence and dependencies between words, making it more effective at learning language patterns. This allows the model to identify and classify spam even in complex and context-dependent messages that traditional methods might misclassify.

The system is deployed using a web-based interface built with Streamlit, where users can input an SMS message and choose a model from a dropdown list. Upon submitting the message, the chosen model processes the input and displays whether the message is spam or not. This flexible and user-friendly architecture not only supports real-time prediction but also provides a practical way to compare the performance of different models. By combining machine learning and deep learning methods, the proposed system offers a scalable and adaptive solution to SMS spam detection that is both accurate and robust.

3.3 FEASIBILITY STUDY

A feasibility study is a critical part of any software development project, conducted to determine whether the proposed system is viable and practical. It assesses the potential of the system from various perspectives technical, economic, and operational to ensure that the project can be successfully developed and implemented. This section presents a comprehensive feasibility analysis for the project titled **“**SMS Spam Detection Using Machine Learning Techniques (LSTM).”

3.3.1. Technical Feasibility

Technical feasibility evaluates whether the current technology and technical resources are sufficient to support the development and implementation of the proposed system.

The SMS spam detection system using Long Short-Term Memory (LSTM) falls well within the capabilities of current software and hardware technologies. LSTM is a type of Recurrent Neural Network (RNN) designed for sequence data such as natural language, and it is widely used in various Natural Language Processing (NLP) tasks like text classification, sentiment analysis, and spam detection.

The tools and technologies required for this project include:

- **Programming Language**: Python, due to its simplicity and strong support for data science and deep learning.
- **Libraries/Frameworks**: Scikit-learn for preprocessing and evaluation.
- **NLP Tools**: NLTK for text cleaning, tokenization, and stop-word removal.
- **Hardware Requirements**: A standard computer with a modern CPU is sufficient for model development. For faster training, especially on large datasets, a system with a GPU (e.g., NVIDIA CUDA-enabled GPU) is beneficial but not mandatory.

The availability of pre-labeled datasets, such as the UCI SMS Spam Collection, further supports the technical feasibility of the project by eliminating the need for manual data annotation. Moreover, the open-source nature of all the required software tools ensures easy access and integration.

In summary, the technologies needed for implementation are mature, well-documented, and readily available, confirming that the system is technically feasible.

3.3.2. Economic Feasibility

Economic feasibility, also known as cost-benefit analysis, evaluates whether the expected benefits of the project justify the financial investment required to build and deploy it.

In the case of this project, the **economic feasibility is high**, primarily because:

- **Development Costs Are Low**: The project uses open-source software tools like Python, TensorFlow, and Scikit-learn, which eliminates licensing costs. Most development work can be carried out on a personal computer, minimizing hardware expenses.
- **No Need for Paid Datasets**: The availability of public datasets, such as the SMS Spam Collection, removes the need for costly data acquisition.
- **Short Development Time**: The system can be developed and tested within a short period, especially with a small development team or as a student project.
- **Minimal Deployment Costs**: Once developed, the model can be deployed in lightweight applications (e.g., a web service or mobile app) with minimal hosting or maintenance costs, especially using free-tier cloud services like Heroku or AWS Free Tier.

From a long-term perspective, the benefits of implementing an effective spam detection system can significantly outweigh the initial development costs. It can enhance user experience, protect users from fraud, and be integrated into larger security frameworks or messaging platforms. Therefore, the project is **economically viable** and offers a high return on investment, especially for academic, educational, or lightweight commercial purposes.

3.3.3. Operational Feasibility

Operational feasibility considers how well the proposed system will function in a real-world environment and whether it can be effectively adopted and maintained by end users and administrators.

The LSTM-based spam detection system is designed to operate as an automated tool for classifying incoming SMS messages as either spam or ham. From an operational standpoint, the system is highly feasible due to the following reasons:

- **Ease of Use**: The system can be integrated with existing messaging applications or run as a background process without user intervention. Users do not need technical expertise to use the system, as it functions autonomously.
- **High Accuracy**: LSTM models are known for their ability to learn long-term dependencies in sequential data. This allows them to outperform traditional models in spam detection, ensuring fewer false positives and negatives.
- **Scalability**: The model can be easily retrained and updated with new data, allowing it to adapt to evolving spam patterns. Additionally, the system can be scaled to handle large volumes of SMS data if required.
- **Maintenance**: The system requires minimal maintenance post-deployment. Periodic retraining with new data can further improve accuracy and adaptability. System updates and model improvements can be rolled out with little disruption to users.

Potential operational challenges include occasional misclassification of messages and the need to periodically retrain the model with fresh data to maintain performance. However, these issues are manageable and do not hinder the practical deployment of the system.

In conclusion, the spam detection system is operationally feasible, offering ease of use, reliability, and the potential for long-term sustainability.

CHAPTER – 4
SOFTWARE REQUIREMENT SPECIFICATION

4.1 REQUIREMENTS SPECIFICATION

The requirements specification outlines the necessary hardware and software components essential for the successful development and deployment of the SMS Spam Detection system. This specification ensures that the application functions optimally and securely when hosted on a web server or run in a local environment. Efficient requirement planning provides a strong foundation for the application, enabling seamless integration, faster execution, and better compatibility with existing technologies. It also ensures that the server environment is stable, secure, and capable of handling the operations and resource demands of the deep learning model used in the project.

4.1.1 Hardware Requirements

The hardware requirements specify each interface of the software elements and the hardware elements of the system. These hardware requirements include configuration characteristics.

Hardware Requirements:

1. Processor : Intel i5(10th Generation or later)

2. Speed : 2.56 GHz

3. RAM : 16 GB

4. Hard Disk : 32 GB

4.1.2 Software Requirements

The software requirements specify the use of all required software products like data management system. The required software product specifies the numbers and version. Each interface specifies the purpose of the interfacing software as related to this software product.

Software Requirements:

1. Operating System: Windows 10 or more
2. Programming Languages: Python
3. Development Environment / IDE: Jupyter Notebook or Visual Studio Code
4. Deep Learning Libraries: TensorFlow, Keras
5. Data Processing Libraries: Pandas, NumPy, Matplotlib
6. Web Framework: Streamlit

7. Package Managers: pip or conda

4.2 FUNCTIONAL REQUIREMENTS

Functional requirements define what the system should do — the core functionalities and features it must support to meet the objectives of the application. These requirements specify the behavior of the system under specific conditions and guide the development process.

1. **Message Input Handling:** The system should allow users to input SMS text either manually or through file uploads for classification.
2. **Spam Detection:** The system must process the input message and classify it as either "Spam" or "Not Spam" using the trained LSTM model.
3. **User Interface Interaction:** The system should provide a simple, interactive interface through which users can enter messages, view classification results, and receive appropriate feedback.
4. **Model Integration:** The backend must integrate the LSTM model effectively, ensuring that real-time predictions are made accurately upon message submission.
5. **Data Preprocessing:** The system must automatically clean, tokenize, and convert the input text into a format suitable for model inference.
6. **Real-Time Prediction:** The system should return prediction results instantly after input, with minimal latency.
7. **Error Handling:** The system should handle invalid inputs or unexpected errors gracefully and provide meaningful messages to the user.
8. **Logging and Monitoring:** The application should log prediction requests and outcomes for monitoring and potential future improvements.

4.3 NON-FUNCTIONAL REQUIREMENTS

Non- functional requirements are the criteria that describe how the system performs rather than what it does. They define system attributes such as usability, scalability, maintainability. Portability, security and reliability.

1. **Usability:** The system should be user-friendly and easy to operate, requiring minimal technical expertise. The user interface must be intuitive, providing clear instructions and feedback regarding the classification results.

2. **Scalability:** The system must efficiently handle increasing volumes of SMS data without performance loss, especially when deployed in environments with high message traffic.

3. **Maintainability:** The codebase should be modular, well-organized, and documented to facilitate easy debugging, updating, or extending by future developers.

4. **Portability:** The application should be platform-independent and capable of running on various operating systems such as Windows, Linux, or cloud-based platforms.

5. **Security:** The system must protect all user data from unauthorized access. Secure connections (e.g., HTTPS, encrypted APIs) should be used for any data exchange with external services or databases.

6. **Reliability:** The system should produce accurate, stable, and consistent results under different conditions and should recover gracefully from unexpected errors.

4.4 PERFORMANCE REQUIREMENTS

The performance of the SMS spam detection system is crucial for its practical usability. One of the key performance requirements is response time the system should be able to process and classify a single SMS message in under one second. This ensures a smooth and responsive experience for end users or applications that rely on real-time spam detection. In terms of model performance, the LSTM-based system should achieve at least 90% accuracy on validation or test datasets to be considered effective. Alongside accuracy, other evaluation metrics like precision and recall are vital. The system should maintain a precision rate above 90% to minimize false positives (i.e., classifying ham as spam) and a recall rate above 85% to ensure that most spam messages are correctly identified.

The training time for the LSTM model should be reasonable ideally less than an hour on standard hardware with faster performance possible when using a GPU. The system should also be resource-efficient, capable of running on computers with basic configurations (e.g., 4 GB RAM and dual-core CPU), though GPU support can significantly enhance model training and prediction speed. These performance standards ensure that the system is both effective and practical for real-world deployment. In addition to classification, the system should allow for retraining or fine-tuning of the LSTM model using new or updated datasets. This functionality is important to ensure the model adapts to emerging spam patterns and continues to perform well over time. Optionally, the system may also include features to store the message history and classification results in a secure database, which can later be used for auditing, analytics, or further training. If the project includes a user interface, it should display the classification result to the user in a clear and timely manner, possibly highlighting suspicious messages or generating notifications for detected spam.

CHAPTER – 5
SYSTEM DESIGN

System design is a crucial phase in the development process where the architecture of the system is planned to ensure efficient, scalable, and maintainable implementation. In the SMS

Spam Detection system, the design follows a modular approach consisting of separate components for data input, preprocessing, model inference, and output display. The system design of the SMS Spam Detection project is structured using a modular and scalable architecture that integrates both traditional machine learning models Naive Bayes, SVM, Random Forest and a deep learning-based LSTM model within a unified framework. The system is developed using Streamlit for the frontend, providing a user-friendly interface that allows users to input SMS messages and select the desired model from a dropdown menu. Upon submission, the message is processed through a backend pipeline that includes a preprocessing module and a model inference module. The preprocessing module performs text cleaning operations such as lowercasing, punctuation removal, and tokenization; for traditional ML models, it applies TF-IDF vectorization, while for the LSTM model, it uses tokenization and sequence padding to prepare the data for deep learning. Once preprocessed, the message is passed to the selected model each stored as a .pkl file for ML models and .h5 for LSTM to generate a prediction indicating whether the message is spam or not. The result is then displayed to the user through the same interface. This decoupled design ensures separation of concerns between the UI, preprocessing, and prediction layers, enabling easy maintenance, extensibility, and deployment. The system is flexible enough to accommodate future improvements such as the integration of additional models, database support, or realtime logging, making it suitable for both research and real-world applications.

5.1 SYSTEM ARCHITECTURE

The system architecture for SMS spam detection is designed to efficiently classify text messages into either “ham” (legitimate) or “spam” (unwanted) categories using both machine learning and deep learning approaches. The process begins with the input dataset, specifically train.csv, which contains labeled SMS messages. This raw data undergoes a structured preprocessing pipeline that includes the elimination of naïve or local language content, removal of headers, timestamps, and contact details, followed by filtering out punctuation, short messages, and prepositions that do not add value to classification. After preprocessing, the clean data is directed into two parallel classification modules. The first module uses traditional machine learning models such as Support Vector Machines (SVM), Random Forest, and Naïve Bayes to classify messages based on learned patterns. The second module leverages deep learning by transforming text into numerical vectors using word embedding techniques and then feeding them into an LSTM (Long Short-Term Memory) network, which excels at learning contextual and sequential dependencies in text data. The outputs from both classification models then lead to the final action: if a message is identified as “ham,” it is allowed to be received by the user, whereas if it is classified as “spam,” it is blocked to prevent unnecessary intrusion. This architecture ensures robust detection by combining the strengths of both traditional and deep learning techniques for accurate SMS spam filtering.

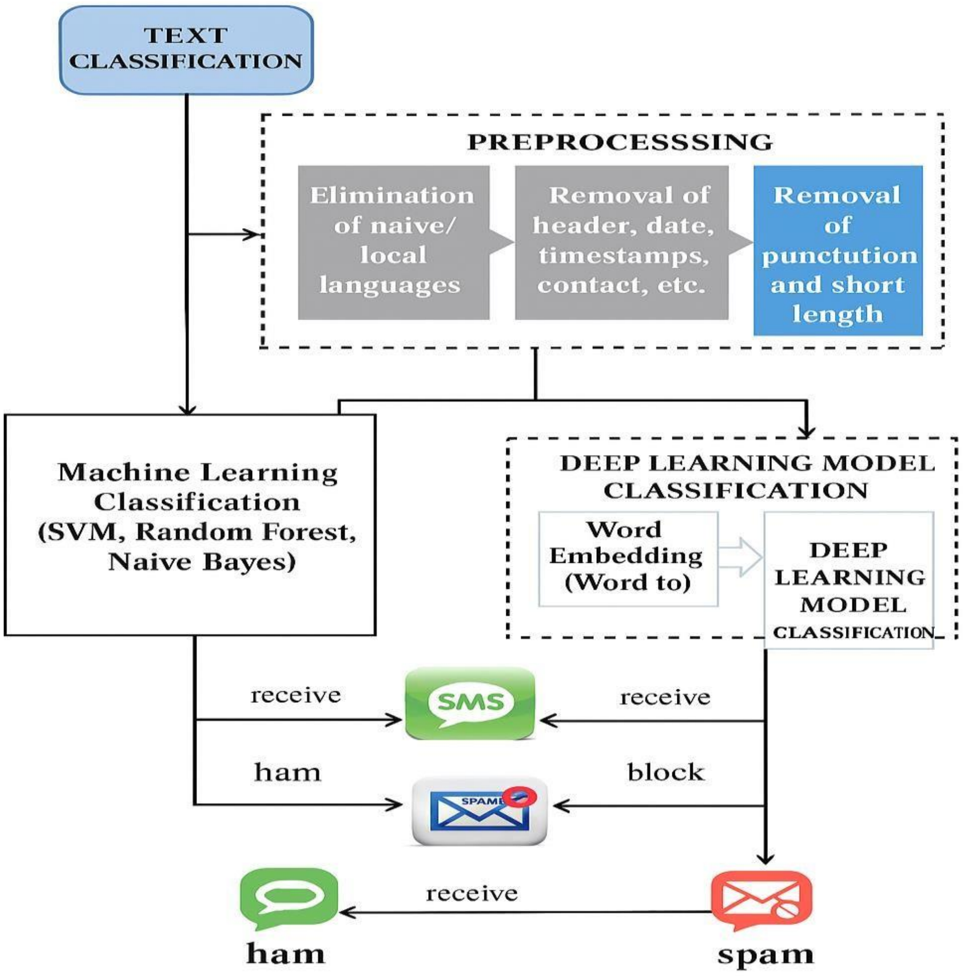

TEXT CLASSIFICATION
PREPROCESSSING
Elimination of naive/ local languages
Removal of header, date, timestamps, contact, etc.
Removal of punctution and short length
Machine Learning Classification (SVM, Random Forest, Naive Bayes)
DEEP LEARNING MODEL CLASSIFICATION
Word Embedding (Word to)
DEEP LEARNING MODEL CLASSIFICATION
receive
SMS
receive
ham
block
SPAM
receive
ham
spam

Fig 5.1. Architecture Diagram

5.2 UML DIAGRAMS

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. UML is a common language for creating models of object-oriented computer software. In its current form UML Is comprised of two major components, i.e., met model and a notation. In the future, some form of method or process may also be added. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems. The UML is a very important part of developing object-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects. The Primary goals in the design of the UML are

i) Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.

ii) Provide extendibility and specialization mechanisms to extend the core concepts.

iii) be independent of particular programming languages and development process. iv) Provide a formal basis for understanding the modeling language.

v) Encourage the growth of OO tools market.

vi) Support higher level development concepts such as collaborations, frameworks, patterns and components.

5.2.1 Use Case Diagram

A use case diagram in the Unified Modelling Language (UML) is a type of behavioural 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.

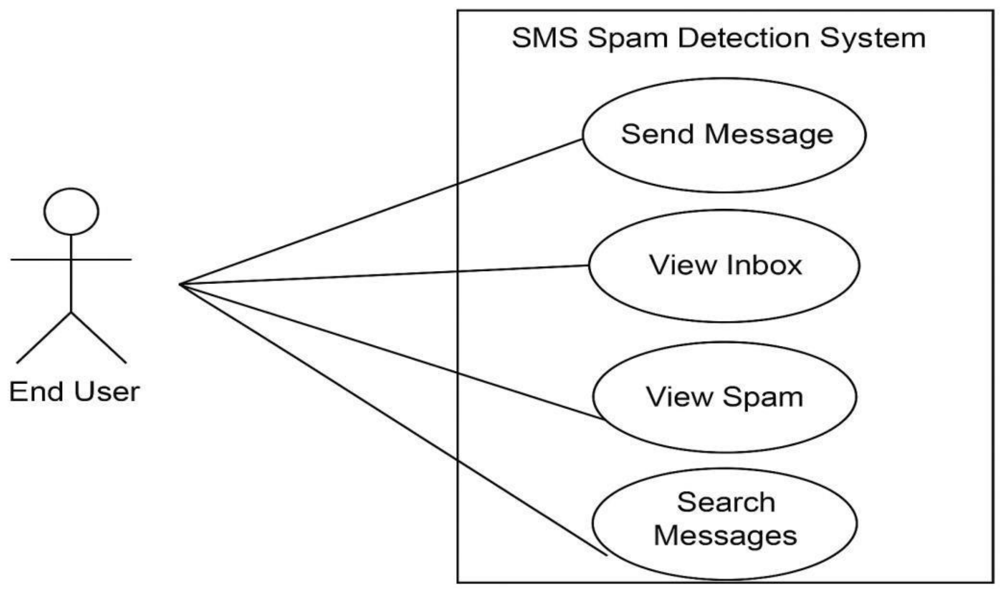


Fig 5.2 Use case diagram for end user

5.2.2 Class Diagram

In software engineering, a class diagram in the Unified Modelling 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. The classes in a class diagram represent both the main objects, interactions in the application and the classes to be programmed. The class is represented with boxes which contain three parts

i) The upperpart holds the name of the class ii) The middle part contains the attributes of the class iii) The bottom part gives the methods or operations the class can take or undertake.

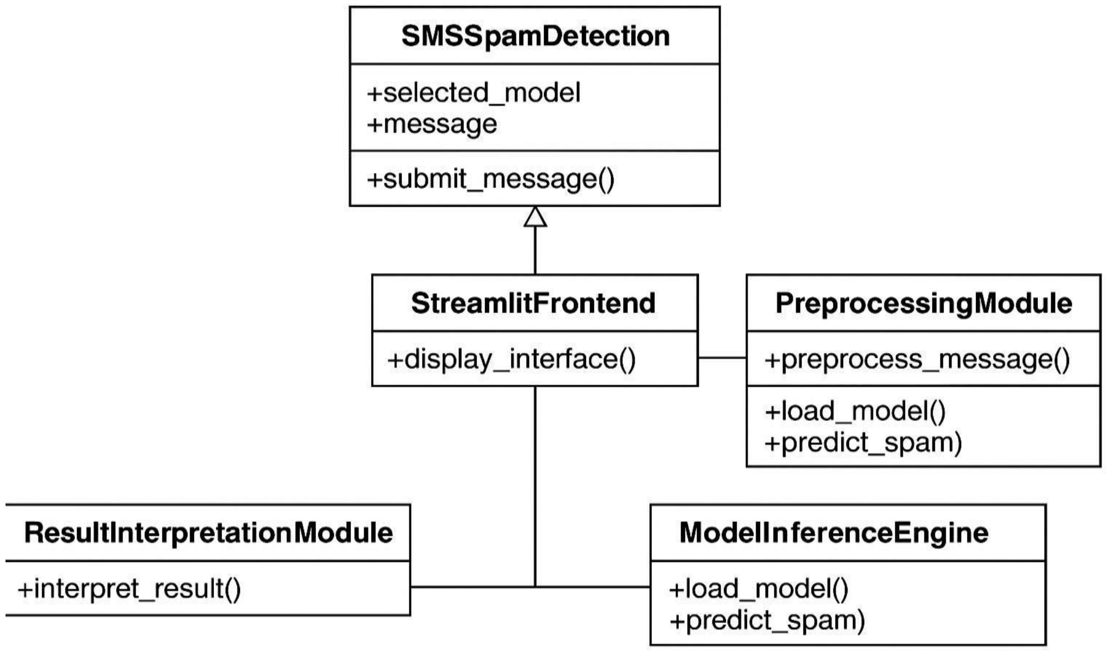


Fig 5.3 Class Diagram

5.2.3 Sequence Diagram

A sequence diagram 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 .A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the Logical View of the system under development. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

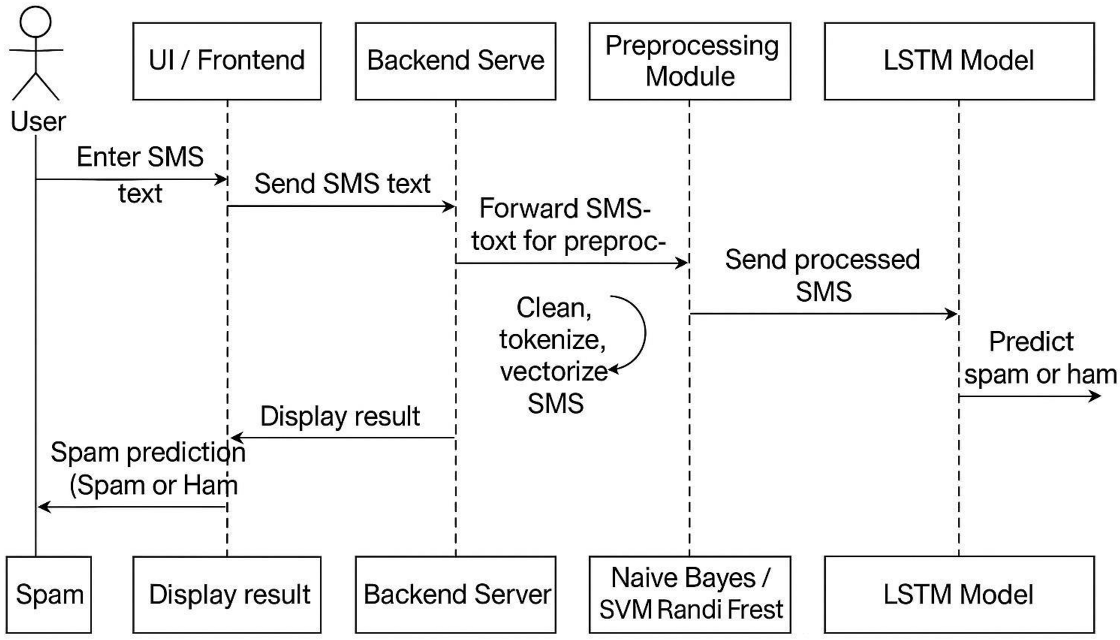


Fig 5.4 Sequence Diagram

5.2.4 Activity Diagram

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

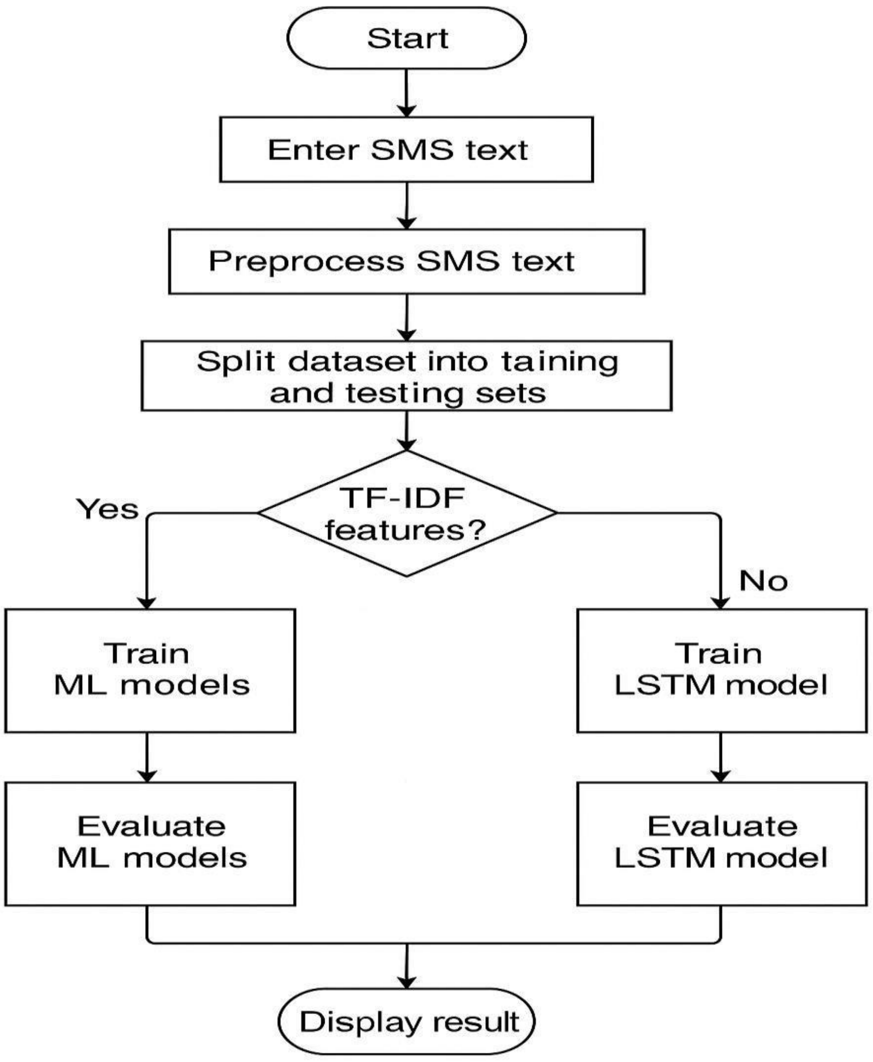


Fig 5.5 Activity Diagram

5.2.5 Component Diagram

Component diagrams are different in terms of nature and behaviour. Component diagrams are used to model the physical aspects of a system. Physical aspects are the elements such as executable, libraries, files, documents, etc. which reside in a node. Component diagrams are used to visualize the organization and relationships among components in a system. These diagrams are also used to make executable systems. Component diagram is a special kind of diagram in UML. The purpose is also different from all other diagrams discussed so far. It does not describe the functionality of the system but it describes the components used to make those functionalities. Thus from that point of view, component diagrams are used to visualize the physical components in a system. These components are libraries, packages, files, etc. Component diagrams can also be described as a static implementation view of a system. Static implementation represents the organization of the components at a particular moment. A single component diagram cannot represent the entire system but a collection of diagrams is used to represent the whole.

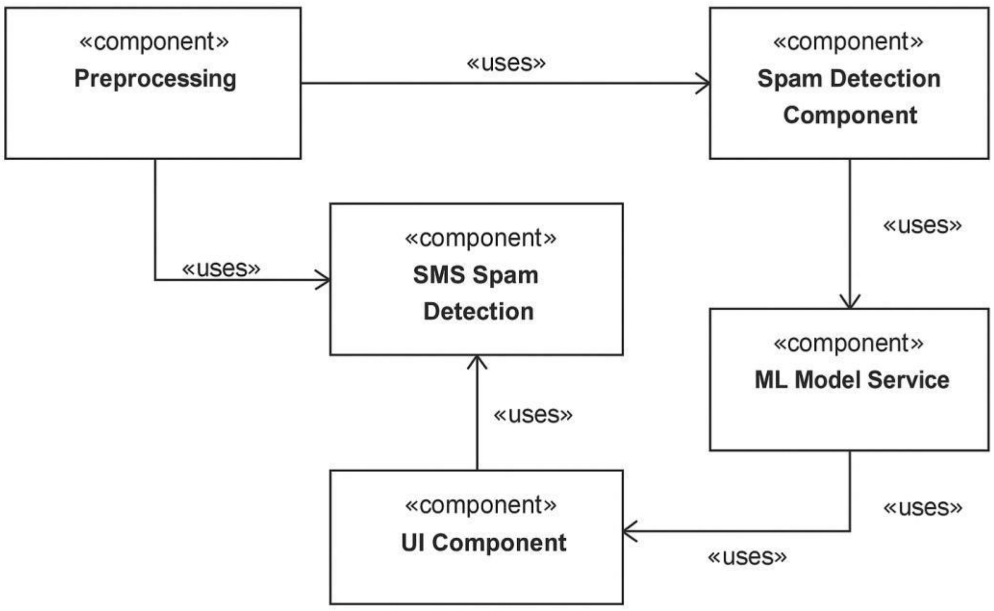

«component» Preprocessing
«uses»
«component» Spam Detection Component
«uses»
«component» SMS Spam Detection
«uses»
«component» ML Model Service
«uses»
«component» UI Component
«uses»
«uses»

Fig 5.6 Component Diagram

5.2.6 Deployment Diagrams

Deployment diagrams are used to visualize the topology of the physical components of a system, where the software components are deployed. These diagrams are used to describe the static deployment view of a system. Deployment diagrams consist of nodes and their relationships. Most of the UML diagrams are used to handle logical components but deployment diagrams are made to focus on the hardware topology of a system. Deployment diagrams are used by the system engineers.

The purpose of deployment diagrams are

- Visualize the hardware topology of a system.

- Describe the hardware components used to deploy software components.
- Describe the runtime processing nodes.

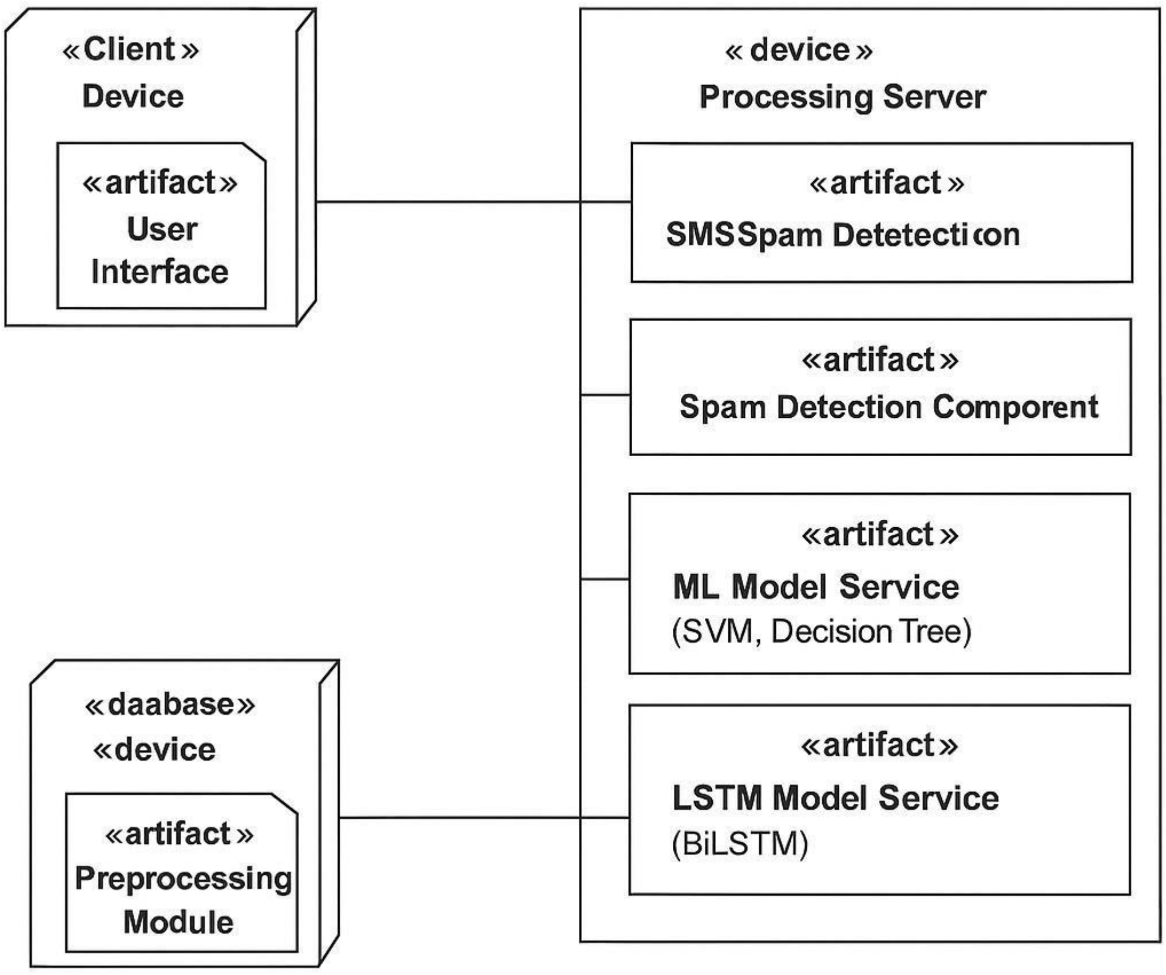


Fig 5.7 Deployment diagram

CHAPTER – 6

IMPLEMENTATION

The SMS Spam Detection project is designed to classify incoming SMS messages as either spam or ham (legitimate) using machine learning techniques. This project includes data preprocessing, model training, evaluation, and deployment through a web interface using Streamlit.

6.1 DATA PREPROCESSING AND MODEL TRAINING

The backend pipeline is implemented using Python, with key libraries including pandas for data handling, NLTK for natural language processing, scikit-learn for machine learning algorithms, and TensorFlow/Keras for deep learning model development. The primary objective is to classify SMS messages as spam or ham using a combination of classical ML models and an LSTM-based deep learning approach.

6.1.1 Dataset Loading and Exploration

The dataset used is the SMS Spam Collection Dataset (train.csv), which contains thousands of real SMS messages labeled as “spam” or “ham”. It is loaded using pandas and explored to assess class distribution and message structure. This exploration step helps ensure data quality and informs the preprocessing and model design choices.

6.1.2 Text Preprocessing

Text preprocessing is crucial for effective model training. The following steps are applied:

1. Lowercasing: Standardizes all messages to lowercase.
2. Noise Removal: Punctuation, special characters, and numbers are stripped.
3. Stopwords Removal**:** Commonly used English words with low semantic value are removed using NLTK’s stopwords.
4. Tokenization: Splitting the message text into individual meaningful tokens.

For LSTM, the tokenized text is further processed using Keras Tokenizer and padded to a uniform sequence length. For traditional ML models, TF-IDF vectorization is applied to convert the text into numerical feature vectors.

6.1.3 Feature Extraction

Two distinct feature extraction approaches are used:

- For **Naive Bayes, SVM, and Random Forest**, TF-IDF is applied to encode the frequency and importance of terms.
- For the **LSTM model**, sequences are tokenized and padded, and then passed to an embedding layer to convert words into dense vector representations that capture semantic meaning.

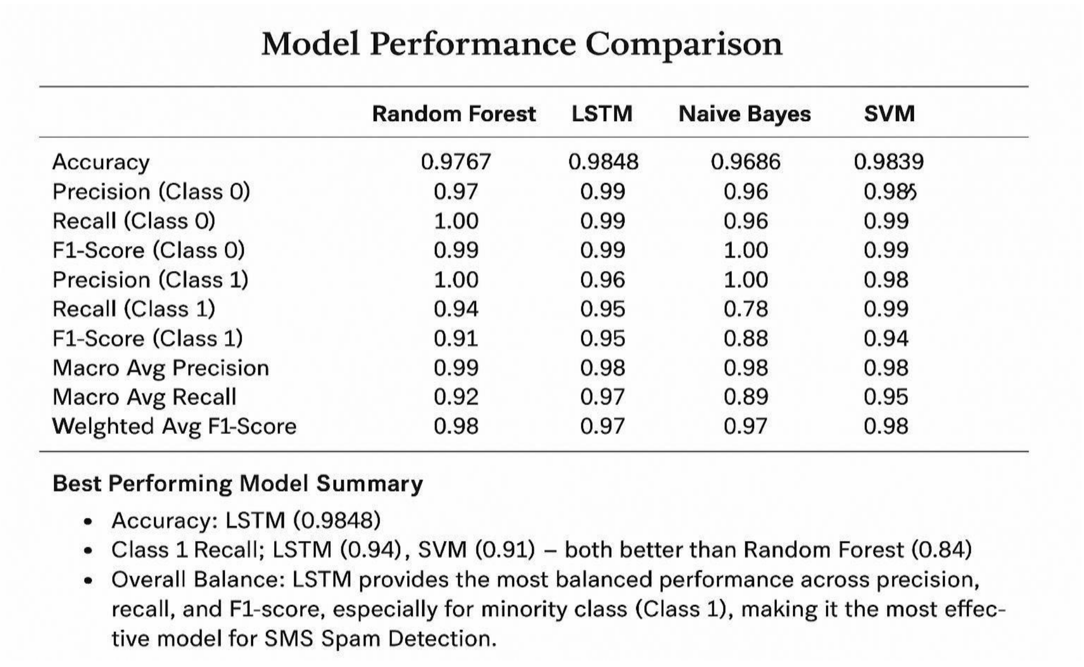
These feature sets are then used to train the corresponding models.

6.1.4 Model Selection and Training

Four models are trained for classification:

- **Naive Bayes:** Fast and effective for basic spam filtering.
- **Support Vector Machine (SVM):** Provides high accuracy with optimal margin separation.
- **Random Forest:** Ensemble-based classifier with strong generalization capability.
- **Long Short-Term Memory (LSTM):** Captures sequential and contextual dependencies in messages.

The dataset is split into training and testing subsets. Each model is trained and evaluated using metrics such as accuracy, precision, recall, and F1-score. The trained models and associated vectorizers/tokenizers are serialized using pickle (for ML models) and .h5 format (for the LSTM model) to be reused in deployment.


Model Performance Comparison

	Random Forest	LSTM	Naive Bayes	SVM
Accuracy	0.9767	0.9848	0.9686	0.9839
Precision (Class 0)	0.97	0.99	0.96	0.985
Recall (Class 0)	1.00	0.99	0.96	0.99
F1-Score (Class 0)	0.99	0.99	1.00	0.99
Precision (Class 1)	1.00	0.96	1.00	0.98
Recall (Class 1)	0.94	0.95	0.78	0.99
F1-Score (Class 1)	0.91	0.95	0.88	0.94
Macro Avg Precision	0.99	0.98	0.98	0.98
Macro Avg Recall	0.92	0.97	0.89	0.95
Welghted Avg F1-Score	0.98	0.97	0.97	0.98

Best Performing Model Summary

- Accuracy: LSTM (0.9848)
- Class 1 Recall; LSTM (0.94), SVM (0.91) – both better than Random Forest (0.84)
- Overall Balance: LSTM provides the most balanced performance across precision, recall, and F1-score, especially for minority class (Class 1), making it the most effective model for SMS Spam Detection.

Fig 6.1 Model Performance Comparison

Model Performance Comparison for SMS Spam Detection To evaluate the effectiveness of various machine learning and deep learning models for SMS spam detection, we compared the performance metrics of four algorithms: Random Forest, LSTM, Naive Bayes, and SVM. The models were assessed based on key evaluation metrics such as Accuracy, Precision, Recall, and F1-Score for both classes (Ham = 0, Spam = 1).

Analysis

LSTM achieved the highest accuracy of 98.48%, making it the most reliable model in correctly predicting both ham and spam messages. SVM and Random Forest also showed strong performance with accuracies of 98.39% and 97.67% respectively. Naive Bayes, while fast and efficient, showed the lowest performance in detecting spam, particularly in terms of recall for spam (0.78). LSTM had the best recall and F1-score for class 1 (Spam), indicating its superiority in detecting spam messages, which is crucial for a spam detection system.

Conclusion

Based on the comprehensive analysis of all key performance indicators, LSTM stands out as the best performing model for SMS spam detection. It offers a balanced trade-off between precision and recall, especially for the spam class, which is the primary focus of this system. •

6.2 MODEL DEPLOYMENT WITH STREAMLIT

The deployment layer is built using **Streamlit**, which provides a fast and lightweight way to deploy machine learning models through an interactive web application.

6.2.1 Application Structure

The Streamlit application loads all required models Naive Bayes, SVM, Random Forest, and LSTM along with the saved TF-IDF vectorizer and Tokenizer. Users are presented with a dropdown menu to select the model and a text input area to enter an SMS message. The system applies the same preprocessing pipeline used during training. Depending on the selected model, the message is vectorized or padded accordingly and passed to the model for prediction. The result is displayed instantly, informing the user whether the message is spam or not.

6.2.2 User Experience Features

The application offers a clean, minimalist UI with helpful input prompts. It includes basic validation to ensure users input meaningful messages and provides real-time predictions. This makes the tool both practical and educational, giving users immediate insight into how different models interpret SMS content.

6.3 CODE ORGANIZATION

The project is modularly structured into the following components:

1. **sms_spam_all_models.ipynb**
   Contains data loading, preprocessing, training, evaluation, and model saving logic for all models (NB, SVM, RF, LSTM).
2. **deploy.py**
   Implements the Streamlit app logic, including model loading, input handling, preprocessing, inference, and result display.
3. **requirements.txt**
   Lists all dependencies such as pandas, nltk, scikit-learn, streamlit, tensorflow, etc.

4. **artifacts/**

   Contains serialized models:

   a. nb_model.pkl
   b. svm_model.pkl
   c. rf_model.pkl
   d. lstm_model.h5

   ...as well as their associated vectorizers:

   e. tfidf_vectorizer.pkl
   f. tokenizer.pkl

6.4 SECURITY AND DATA PRIVACY CONSIDERATIONS

Although this project primarily focuses on machine learning techniques, it follows essential best practices to ensure the security and privacy of user data. User input is handled carefully, avoiding unnecessary storage of sensitive information to minimize potential data leaks. The deployed application is designed to prevent exposure of any personal or confidential data. Additionally, to protect the system from misuse or automated attacks when deployed publicly, security measures such as rate limiting and CAPTCHA verification are incorporated. These steps help maintain the integrity and trustworthiness of the system while respecting user privacy.

6.5 EXTENSIONS AND FUTURE WORK

Future extensions of the system include enhancing the LSTM architecture with bidirectional layers, attention mechanisms, or integrating transformer models like BERT to improve semantic understanding. Multilingual support can expand the tool’s usability across diverse linguistic regions. Introducing a feedback loop where user corrections are logged and used for future model retraining can lead to continuous improvement. Additionally, developing a REST API for the classification system could enable integration with real-world messaging apps and security services, significantly enhancing its practical impact.

6.6 SAMPLE CODE

6.6.1 sms_spam.py

```
!pip install numpy pandas tensorflow nltk scikit-learn import
pandas as pd
# Load the dataset to examine its structure
file_path = '/content/train.csv' data =
pd.read_csv(file_path)


# Display the first few rows of the dataset to understand its structure data.head()
import pandas as pd import numpy as np import re import nltk from nltk.corpus
import stopwords from sklearn.model_selection import train_test_split from
sklearn.feature_extraction.text import TfidfVectorizer from sklearn.naive_bayes
import MultinomialNB from sklearn.svm import LinearSVC from
sklearn.ensemble import RandomForestClassifier from sklearn.metrics import
accuracy_score, classification_report from tensorflow.keras.models import
Sequential from tensorflow.keras.layers import Embedding, LSTM, Dense,
SpatialDropout1D from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences


# Ensure NLTK resources are available
nltk.download('stopwords') nltk.download('punkt')


# Load the dataset file_path = "train.csv"  # Make sure
this path is correct data = pd.read_csv(file_path)
```

```
# Preprocess: Remove NaNs and clean the text data.dropna(subset=['sms',
'label'], inplace=True)

# Text cleaning function def preprocess_text(text):     stop_words =
set(stopwords.words('english')) - {'won', 'gift', 'call', 'free', 'prize'}     text =
re.sub(r'\W', ' ', text)     text = text.lower()     text = re.sub(r'\s+', ' ', text)     text =
re.sub(r'\d+', '', text)     return ' '.join(word for word in text.split() if word not in
stop_words) data['sms'] = data['sms'].apply(preprocess_text)

# Split for ML models
X_train_raw,   X_test_raw,   y_train,   y_test   =   train_test_split(data['sms'],   data['label'],
test_size=0.2, random_state=42)

# TF-IDF Vectorization tfidf
= TfidfVectorizer()
X_train_tfidf = tfidf.fit_transform(X_train_raw)
X_test_tfidf = tfidf.transform(X_test_raw)

# --------- Model 1: Naive Bayes ----------
nb = MultinomialNB()
nb.fit(X_train_tfidf, y_train) nb_pred =
nb.predict(X_test_tfidf)
```

# --------- Model 2: SVM ---------- svm

= LinearSVC() svm.fit(X_train_tfidf,

y_train) svm_pred =

svm.predict(X_test_tfidf)

# --------- Model 3: Random Forest ---------- rf =

RandomForestClassifier(n_estimators=100, random_state=42)

rf.fit(X_train_tfidf, y_train) rf_pred = rf.predict(X_test_tfidf)

# --------- Model 4: LSTM ---------- #

Tokenization and sequence padding

tokenizer = Tokenizer()

tokenizer.fit_on_texts(data['sms'])

X_seq = tokenizer.texts_to_sequences(data['sms']) max_len

= 50

X_pad = pad_sequences(X_seq, maxlen=max_len)

X_train_lstm, X_test_lstm, y_train_lstm, y_test_lstm = train_test_split(X_pad, data['label'].values, test_size=0.2, random_state=42)

vocab_size = len(tokenizer.word_index) + 1

model = Sequential([

    Embedding(vocab_size, 128, input_length=max_len),

```
    SpatialDropout1D(0.3),

    LSTM(100, dropout=0.2, recurrent_dropout=0.2),

    Dense(1, activation='sigmoid')

])


# Tokenization and sequence padding tokenizer

= Tokenizer()

tokenizer.fit_on_texts(data['sms'])

X_seq = tokenizer.texts_to_sequences(data['sms'])
max_len = 50

X_pad = pad_sequences(X_seq, maxlen=max_len)


# Split for LSTM model

X_train_lstm,  X_test_lstm,   y_train_lstm,  y_test_lstm    =    train_test_split(X_pad,
data['label'].values, test_size=0.2, random_state=42)


vocab_size = len(tokenizer.word_index) + 1


model = Sequential([

    Embedding(vocab_size, 128, input_length=max_len),

    SpatialDropout1D(0.3),

    LSTM(100, dropout=0.2, recurrent_dropout=0.2),

    Dense(1, activation='sigmoid')

])
```

```
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

model.fit(X_train_lstm, y_train_lstm, epochs=5, batch_size=32,
validation_data=(X_test_lstm, y_test_lstm), verbose=1)


# LSTM Prediction lstm_pred = (model.predict(X_test_lstm) >

0.5).astype("int32")

# --------- Evaluation --------- print("\n---

Naive Bayes ---") print("Accuracy:",

accuracy_score(y_test, nb_pred))

print(classification_report(y_test,

nb_pred))


print("\n--- SVM ---") print("Accuracy:",

accuracy_score(y_test, svm_pred))

print(classification_report(y_test, svm_pred))


print("\n--- Random Forest ---") print("Accuracy:",

accuracy_score(y_test, rf_pred))

print(classification_report(y_test, rf_pred))


print("\n--- LSTM ---") print("Accuracy:",

accuracy_score(y_test_lstm, lstm_pred))

print(classification_report(y_test_lstm, lstm_pred))
```

```
import pickle # Save Naive Bayes
model with open('nb_model.pkl',
'wb') as f:
    pickle.dump(nb, f)

# Save SVM model with
open('svm_model.pkl', 'wb') as f:
    pickle.dump(svm, f)

# Save Random Forest model with
open('rf_model.pkl', 'wb') as f:
    pickle.dump(rf, f)

# Save TF-IDF vectorizer with
open('tfidf_vectorizer.pkl', 'wb') as f:
    pickle.dump(tfidf, f)

# Save Tokenizer with
open('tokenizer.pkl', 'wb') as f:
    pickle.dump(tokenizer, f)

model.save('lstm_model.h5')
```

```
# Example Prediction example_sms = "Congratulations! You've won a $1000

Walmart gift card. Call now!" print("\nExample Prediction:") print(f"Message:

{example_sms}") print(f"Prediction: {predict_spam(example_sms)}")


print(predict_spam("Congratulations! You've won a free trip to Paris!"))
print(predict_spam("Hey, let's catch up tomorrow!"))
```

6.6.2 deploy.py

```
import streamlit as st import pickle import numpy as np import os

from tensorflow.keras.models import load_model from

tensorflow.keras.preprocessing.sequence import pad_sequences


st.set_page_config(page_title="SMS Spam Detection", layout="centered") st.title("

SMS Spam Detection App")


# Load models and artifacts

@st.cache_resource def

load_artifacts():

    nb_model = pickle.load(open("nb_model.pkl", "rb"))     svm_model

= pickle.load(open("svm_model.pkl", "rb"))     rf_model =

pickle.load(open("rf_model.pkl", "rb"))     tfidf =

pickle.load(open("tfidf_vectorizer.pkl", "rb"))     tokenizer =

pickle.load(open("tokenizer.pkl", "rb"))     lstm_model =

load_model("lstm_model.h5")     return nb_model, svm_model,
rf_model, tfidf, tokenizer, lstm_model nb_model, svm_model,

rf_model, tfidf, tokenizer, lstm_model = load_artifacts()



# Dropdown to choose model model_choice = st.selectbox("Select a Model", ["Naive
Bayes", "SVM", "Random Forest", "LSTM"])


# Text input for SMS user_input = st.text_area("Enter SMS message to
classify", height=150)


# Prediction on button click
if st.button("Predict"):     if
not user_input.strip():
        st.warning("  Please enter a message first.")
    else:
        if model_choice == "LSTM":
            sequence = tokenizer.texts_to_sequences([user_input])
padded_seq = pad_sequences(sequence, maxlen=50)
prediction = lstm_model.predict(padded_seq)[0][0]             label
= "Spam" if prediction > 0.5 else "Not Spam"
        else:
            vectorized   =   tfidf.transform([user_input])
if model_choice == "Naive Bayes":
        label = "Spam" if nb_model.predict(vectorized)[0] == 1 else "Not Spam"
elif model_choice == "SVM":

        label = "Spam" if svm_model.predict(vectorized)[0] == 1 else "Not Spam"

else:  # Random Forest          label = "Spam" if rf_model.predict(vectorized)[0]

== 1 else "Not Spam"


    st.success(f"  Prediction: **{label}**")
```

CHAPTER – 7
TESTING

Testing is the process where the test data is prepared and is used for testing the modules individually and later the validation given for the fields. Then the system testing takes place which makes sure that all components of the system property functions as a unit. The test data should be chosen such that it passed through all possible condition. The following is the description of the testing strategies, which were carried out during the testing period.

7.1 SYSTEM TESTING

Testing has become an integral part of any system or project especially in the field of information technology. The importance of testing is a method of justifying, if one is ready to move further, be it to be check if one is capable to with stand the rigors of a particular situation cannot be underplayed and because of this reason testing before development is so critical. When the software is developed before it is given to user the software must be tested whether it is solving the purpose for which it is developed. This testing involves various types through which one can ensure the software is reliable. The program was tested logically and pattern of execution of the program for a set of data are repeated. Thus the code was exhaustively checked for all possible correct data and the outcomes were also checked**.**

7.2 MODULE TESTING

To locate errors, each module is tested individually. This enables us to detect error and correct it without affecting any other modules. Whenever the program is not satisfying the required function, it must be corrected to get the required result. Thus all the modules are individually tested from bottom up starting with the smallest and lowest modules and proceeding to the next level. Each module in the system is tested separately. For example the job classification module is tested separately. This module is tested with different jo band its approximate execution time and the result of the test is compared with the results that are prepared manually. Each module in the system is tested separately. In this system the resource classification and job scheduling modules are tested separately and their corresponding results are obtained which reduces the process waiting time.

Test Case Id	Test Case Name	Rest Case Desc.	Test Steps	Expected Output	Actual Output	Test Case Status	Test Priority
01	Upload SMS Dataset	Verify if the dataset is loaded successfully	If dataset is uploaded,show file loaded message	File is loaded and ready for processing	File is loaded successfully	Pass	High
02	Data preprocessing	Verify preprocessing of SMS text	Apply cleaning(remove stopwords,punctuation)	Display cleaned/ Processed data	Cleaned data displayed	Pass	High
03	Train LSTM Model	Train model on SMS dataset	Train model on Training data	Training completed with acceptable loss and accuracy	Model trained with 95% accuracy	Pass	High
04	Predict SMS Label	Check if SMS is correctly classified	Input sample SMS to prediction function	Output label: spam or ham	Correct label returned	Pass	High
05	Evaluate Model Accuracy	Validate model performance	Run evaluation metrics(accuracy,precision, Recall)	Display metrics above 90%	Accuracy 94% Precision 91%	Pass	High
06	Handle Empty Input	Verify system response to empty SMS input	Submit an empty SMS to the classifier	System should return an error or a warning	Warning shown for empty input	Pass	Medium
07	Save and Load Model	Check if the trained model can be saved/loaded	Save the trained model and reload it for prediction	Model Successfully saved and reloaded	Model saved and reloaded without errors	Pass	Medium

Table 7.1 Test Cases

7.3 INTEGRATION TESTING

After the module testing, the integration testing is applied. When linking the modules there may be chance for errors to occur, these errors are corrected by using this testing. In this system all modules are connected and tested. The testing results are very correct. Thus the mapping of jobs with resources is done correctly by the system.

7.4 ACCEPTANCE TESTING

When user finds no major problems with its accuracy, the system passes through a final acceptance test. This test confirms that the system needs the original goals, objectives and requirements established during analysis without actual execution which elimination wastage of time and money acceptance tests on the shoulders of users and management, it is finally acceptable and ready for the operation.

CHAPTER – 8

OUTPUT SCREENS

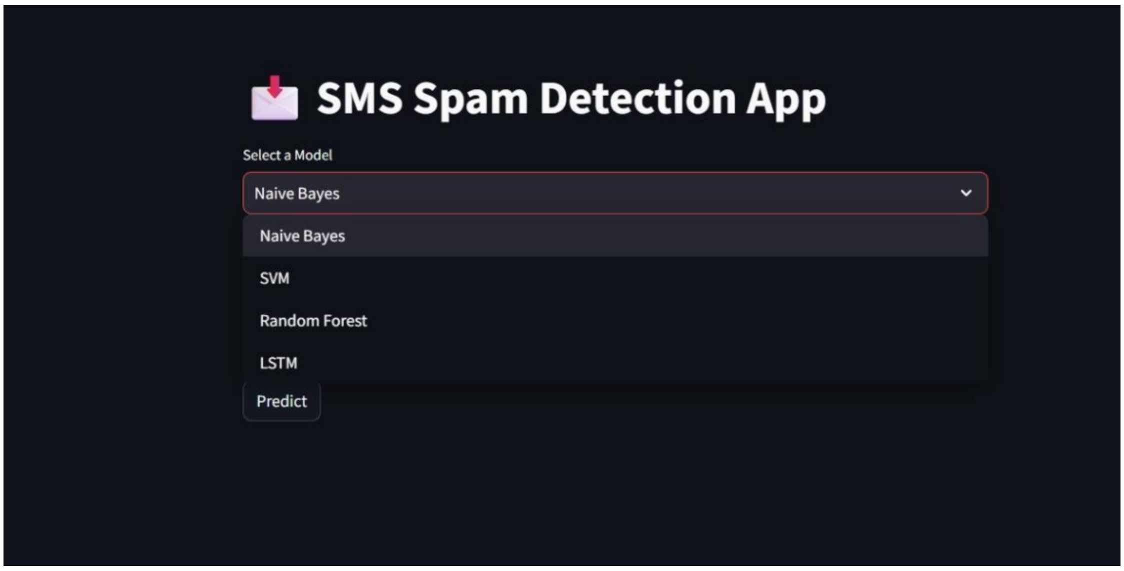
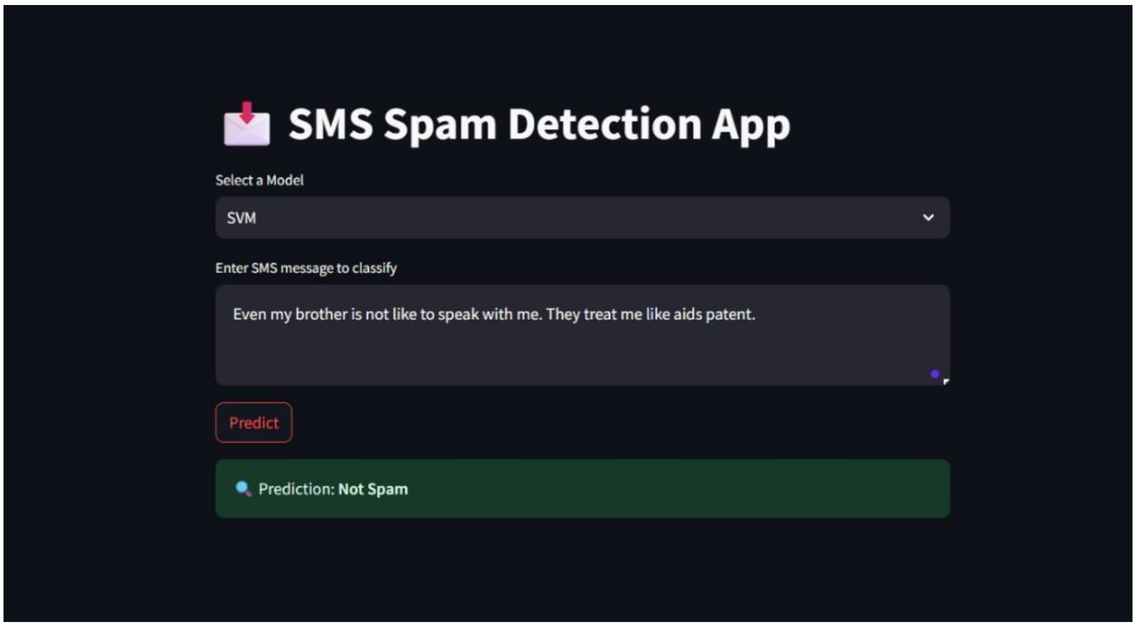


Fig 8.1 Home page



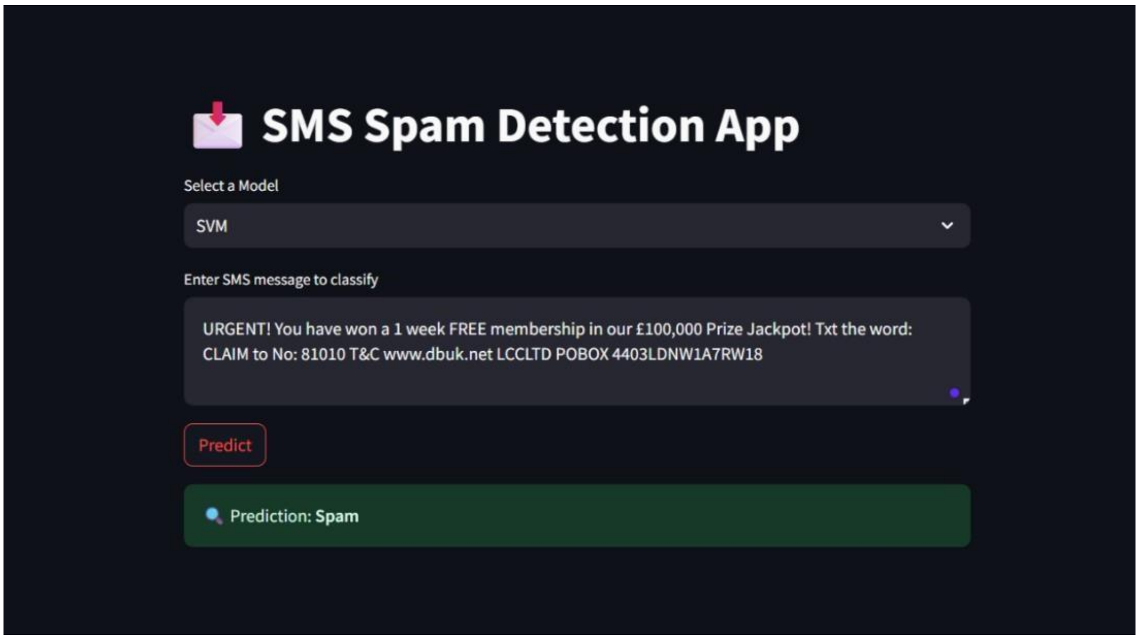
Select a Model: SVM

Enter SMS message to classify

Even my brother is not like to speak with me. They treat me like aids patent.

Prediction: **Not Spam**

Fig 8.2 Ham Message Prediction by SVM


SMS Spam Detection App

Select a Model

SVM

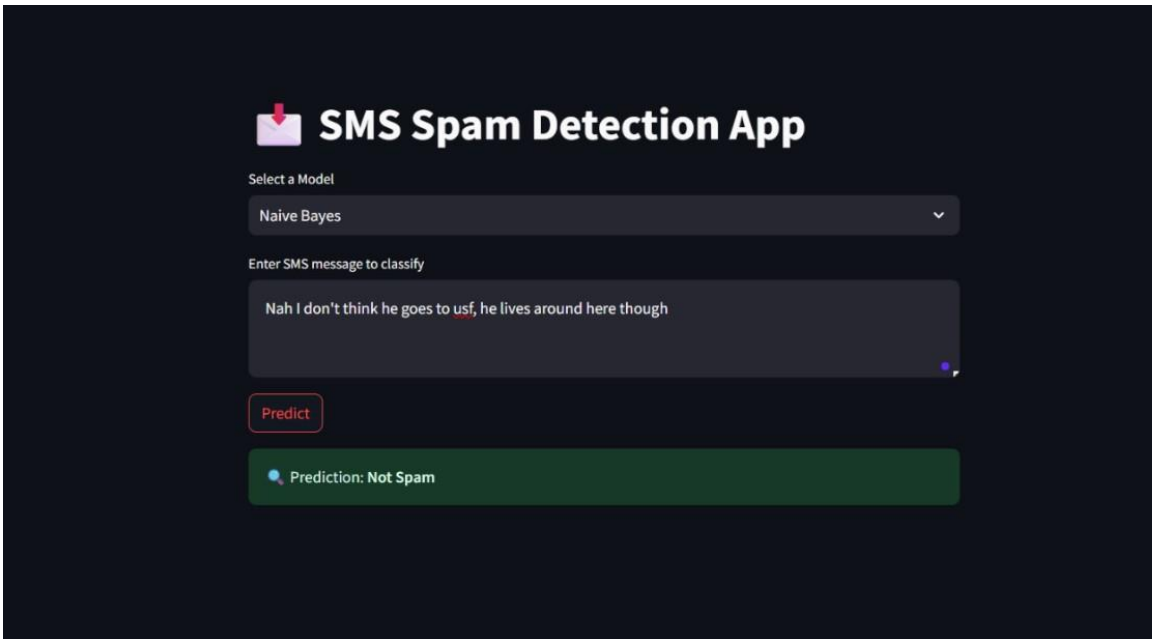
Enter SMS message to classify

URGENT! You have won a 1 week FREE membership in our £100,000 Prize Jackpot! Txt the word: CLAIM to No: 81010 T&C www.dbuk.net LCCLTD POBOX 4403LDNW1A7RW18

Predict

Prediction: **Spam**

Fig 8.3 Spam Message Prediction by SVM


SMS Spam Detection App

Select a Model

Naive Bayes

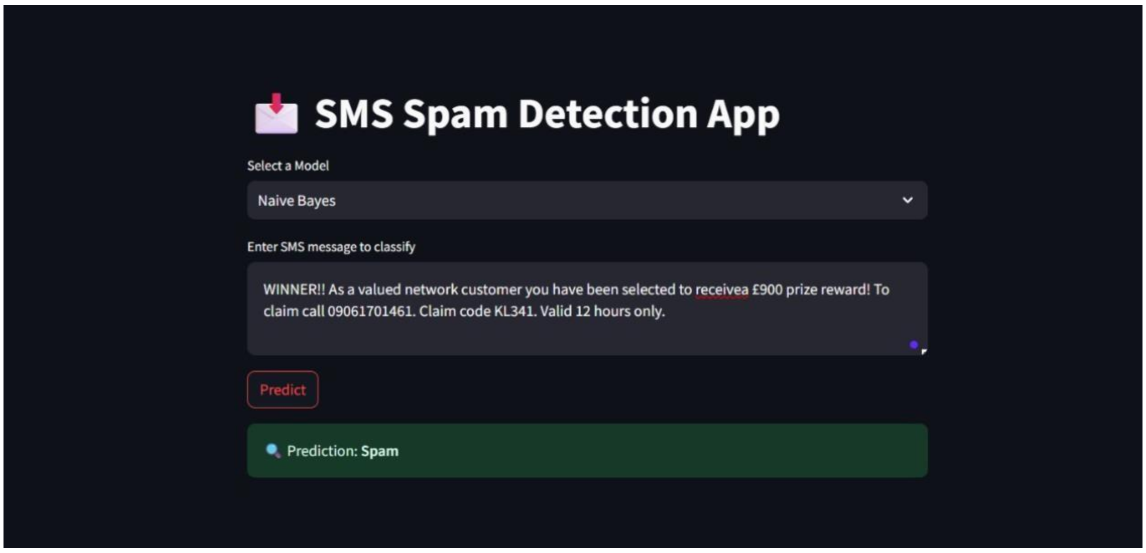
Enter SMS message to classify

Nah I don't think he goes to usf, he lives around here though

Predict

Prediction: **Not Spam**

Fig 8.4 Ham Message Prediction by Naïve Bayes



SMS Spam Detection App

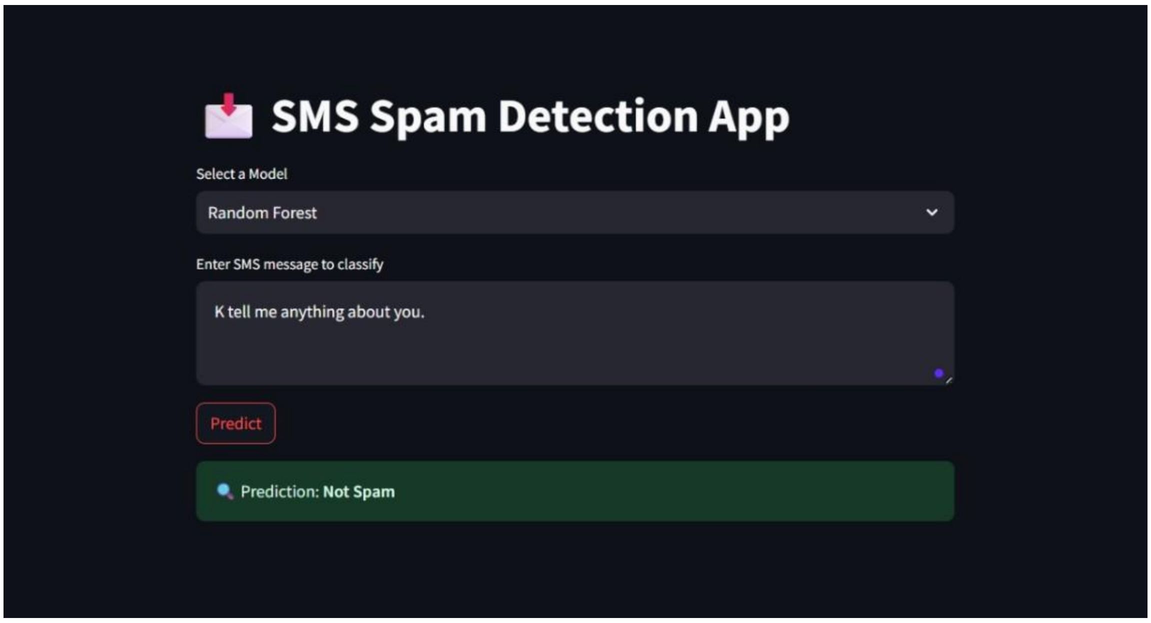
Select a Model: Naive Bayes

Enter SMS message to classify

WINNER!! As a valued network customer you have been selected to receivea £900 prize reward! To claim call 09061701461. Claim code KL341. Valid 12 hours only.

Prediction: **Spam**

Fig 8.5 Spam Message Prediction by Naïve Bayes



SMS Spam Detection App

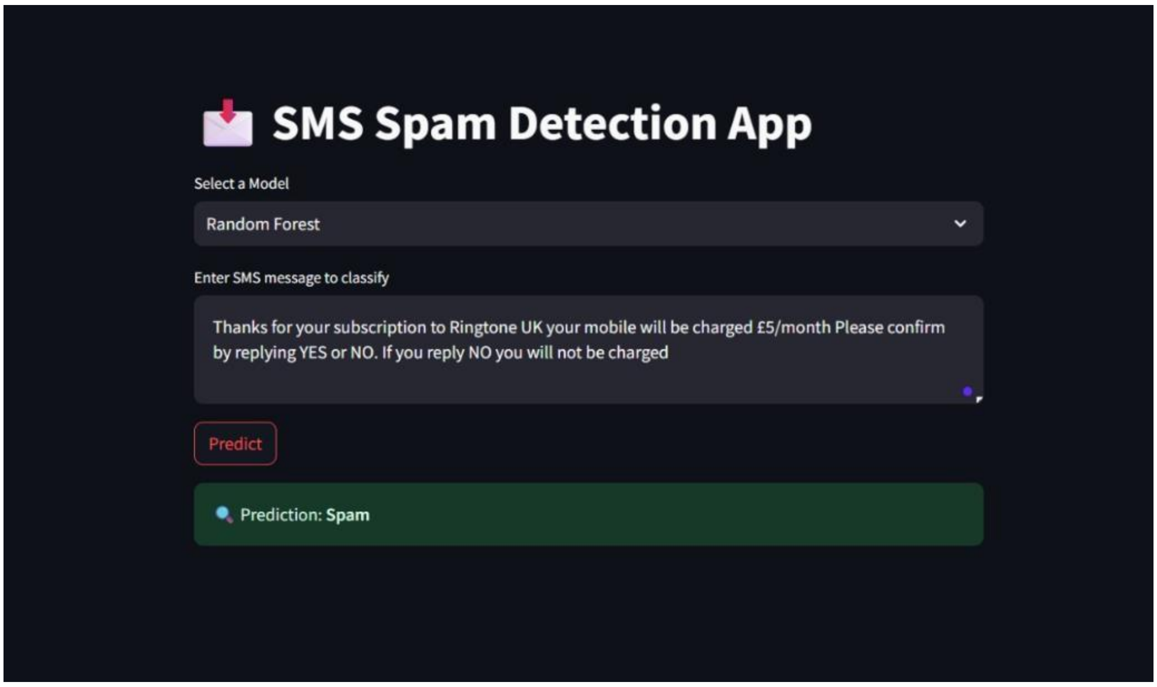
Select a Model: Random Forest

Enter SMS message to classify

K tell me anything about you.

Prediction: **Not Spam**

Fig 8.6 Ham Message Prediction by Random Forest


SMS Spam Detection App

Select a Model

Random Forest

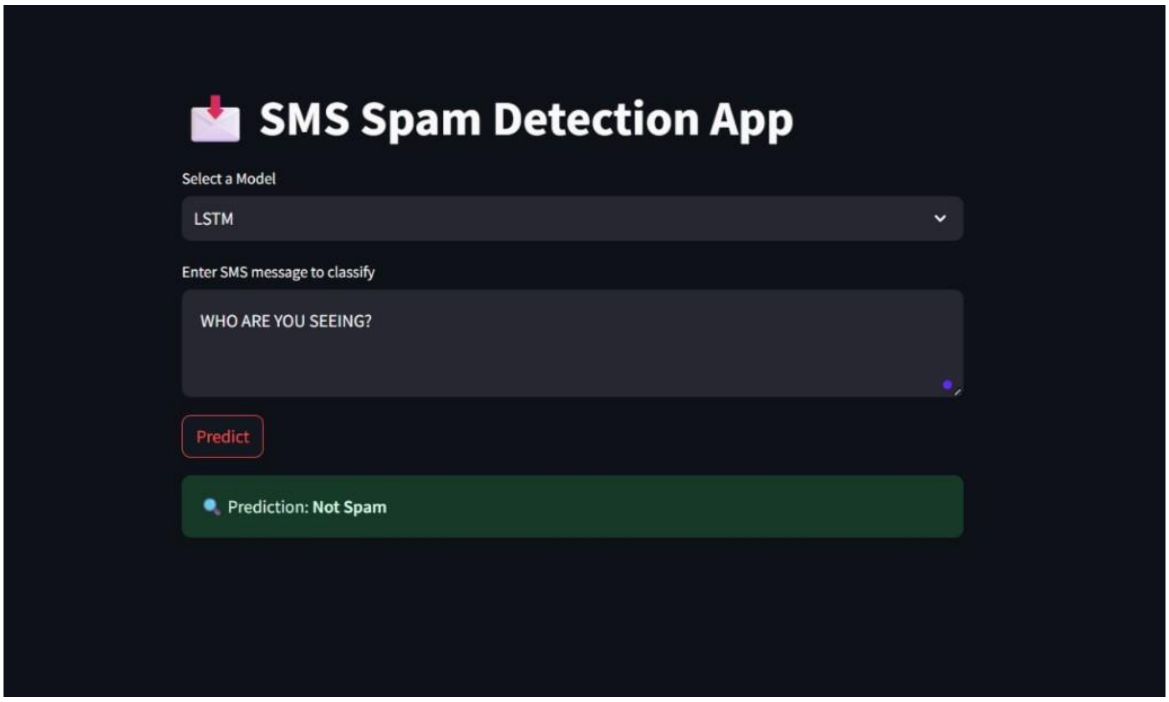
Enter SMS message to classify

Thanks for your subscription to Ringtone UK your mobile will be charged £5/month Please confirm by replying YES or NO. If you reply NO you will not be charged

Predict

Prediction: **Spam**

Fig 8.7 Spam Message Prediction by Random Forest


SMS Spam Detection App

Select a Model

LSTM

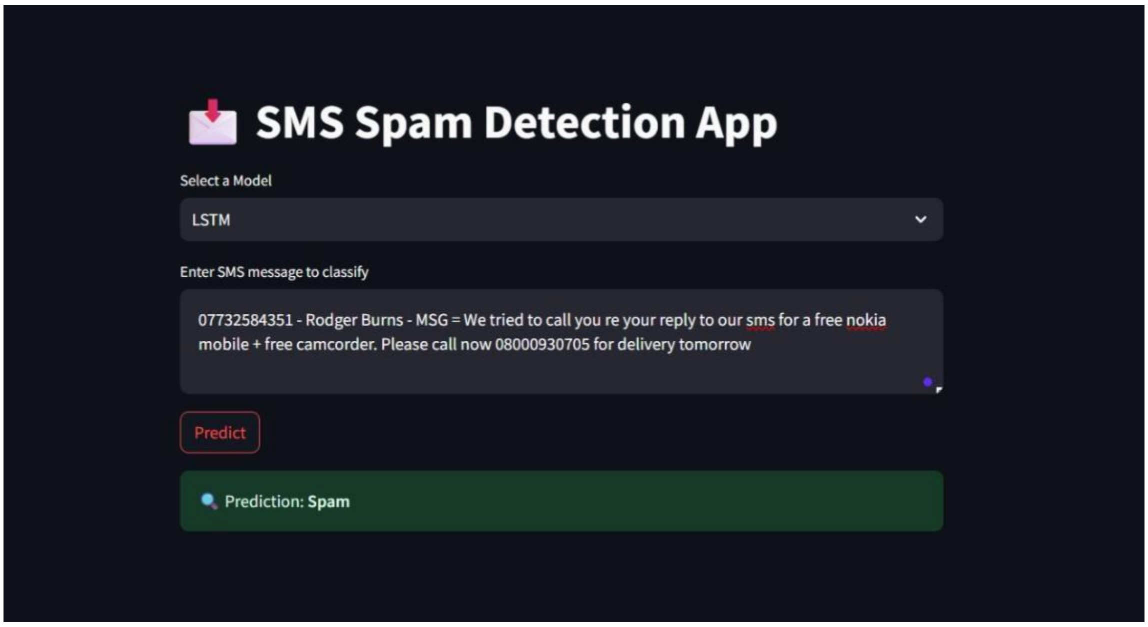
Enter SMS message to classify

WHO ARE YOU SEEING?

Predict

Prediction: **Not Spam**

Fig 8.8 Ham Message Prediction by LSTM


SMS Spam Detection App

Select a Model

LSTM

Enter SMS message to classify

07732584351 - Rodger Burns - MSG = We tried to call you re your reply to our sms for a free nokia mobile + free camcorder. Please call now 08000930705 for delivery tomorrow

Predict

Prediction: **Spam**

Fig 8.9 Spam Message Prediction by LSTM

CHAPTER – 9
CONCLUSION AND FUTURE SCOPE

9.1 CONCLUSION

In conclusion, The rise in SMS spam highlights the need for intelligent detection systems that go beyond basic rule-based methods. This project addresses that challenge by implementing a comprehensive classification framework using both classical machine learning models Naive Bayes, SVM, and Random Forest and a deep learning-based LSTM model. By combining TF-IDF vectorization for traditional models and sequence tokenization for the LSTM, the system effectively captures both statistical and contextual features of messages.

Each model was trained on a real-world dataset and evaluated for performance. While classical models offered quick and interpretable results, the LSTM model showed superior understanding of word sequences and message semantics. The modular design, deployed through a user-friendly Streamlit interface, ensures scalability and ease of use. Overall, the system presents a practical hybrid solution for enhancing SMS spam detection and improving digital communication safety.

9.2 FUTURE SCOPE

Going forward, this project can be extended in several meaningful directions to make it more robust and widely applicable. One such enhancement is the integration with real-time SMS gateways and APIs, which would allow the system to process and classify messages on-thefly. Additionally, support for regional and multilingual messages can be incorporated using translation models or multilingual embeddings, making the solution more inclusive and effective across diverse user bases.

Further improvements could involve exploring advanced deep learning models like Bidirectional LSTM, GRU, or even transformer-based architectures such as BERT to improve semantic comprehension. Incorporating a user feedback loop would allow the system to continuously learn from misclassifications and evolve over time.

CHAPTER - 10 REFERENCES

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