# DEVELOPING A TRANSFORMER BASED MODEL FOR DETECTING SMS SPAM

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## ABSTRACT:

Our goal in writing this study is to investigate whether or not the Transformer model may be used to identify spam SMS messages by suggesting a tweaked version of the model specifically for this purpose. In order to put our proposed spam Transformer to the test, we use UtkMl's Twitter Spam Detection Competition dataset and SMS Spam Collection v.1 dataset. We measure ourselves against state-of-the-art approaches to SMS spam detection and a slew of popular machine learning classifiers. In our research on SMS spam detection, the proposed enhanced spam Transformer performed better than all other choices with a recall of 0.9451%, an accuracy of 98.92%, and an F1-Score of 0.9613 percent. Also, the suggested model does well on UtkMl's Twitter dataset, which bodes well for applying it to other comparable issues.

**INDEX: sms, spam, detection**

## INTRODUCTION:

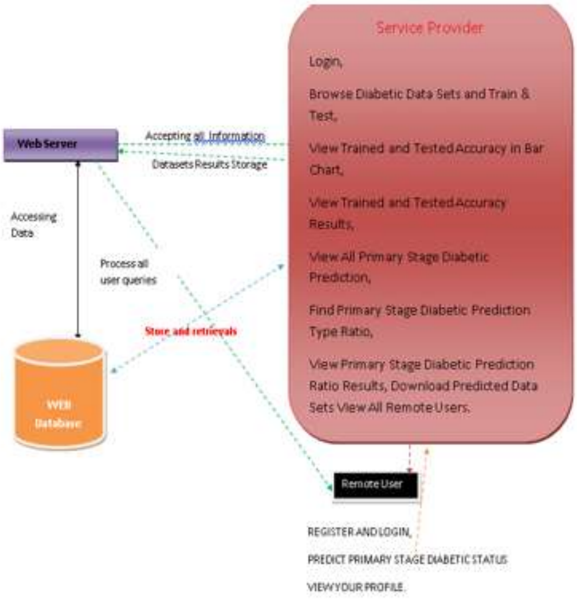
The proliferation of mobile phones and mobile networks in the last few decades has led to the widespread use of the Short Message Service (SMS) as a means of communication. Nevertheless, SMS spam is a problem for SMS users as well. Any pointless messages sent over mobile networks are considered SMS spam, often called intoxicated message [1]. Spam mails are extremely popular for a variety of reasons. To start, the potential number of people targeted by a spam message assault is significant since there are a many individuals utilizing cell phones across the globe. In addition, spammers may be pleased to hear that sending out spam doesn't cost much. Finally, most mobile phones' severely limited processing capabilities mean that their spam classifiers can't do a very good job of recognising spam messages.

Machine learning has been a hot subject for the last few decades, and it has found several uses in categorization across many different fields of study. To be more specific, spam detection is an area of study that has been around for a while and has a number of tried and true approaches. Some machine learning classifiers relied on manually derived features from training data, although this wasn't the case for the majority of them [2].

Profound learning is a subfield of AI that has been blasting as of late, moved by the outstanding expansion in figuring control over the course of the past years and years. Applications based on deep learning are increasingly important in modern culture, simplifying many parts of our lives. The application of Recurrent Neural Networks (RNNs) and its derivatives, such as Long Short-Term Memory (LSTM), to spam detection has been very successful in recent years. RNNs are among the most popular and effective deep learning architectures.

Successful English-German and English-French translations were the initial goal of the attention-based sequence-to-sequence paradigm known as the Transformer [3]. Also, other new models based on Transformers have been suggested to solve various NLP issues; for example, BERT [5] and GPT-3 [4]. The success and potential of the Transformer series have been validated by their many achievements. The purpose of this work is to investigate the feasibility of using the Transformer model to the challenge of SMS spam identification. Hence, to detect SMS spam, we suggest a tweaked model that is based on the vanilla Transformer. In addition, we evaluate and contrast the efficacy of conventional ML classifiers, a long short-term memory (LSTM) profound learning approach, and the spam Transformer model that we have created for detecting spam in SMS.

## SYSTEM ARCHITECTURE


Service Provider
Login,
Browse Diabetic Data Sets and Train & Test,
View Trained and Tested Accuracy in Bar Chart,
View Trained and Tested Accuracy Results,
View All Primary Stage Diabetic Prediction,
Find Primary Stage Diabetic Prediction Type Ratio,
View Primary Stage Diabetic Prediction Ratio Results, Download Predicted Data Sets View All Remote Users.
Web Server
Accepting all Information
Datasets Results Storage
Accessing Data
Process all user queries
Store and retrievals
Web Database
Remote User
REGISTER AND LOGIN,
PREDICT PRIMARY STAGE DIABETIC STATUS
VIEW YOUR PROFILE.

## METHODOLOGY

### Data set:

In the experiments, two different datasets are utilized. The first dataset is SMS Spam Collection v.1 [13] dataset, which is labeled SMS messages dataset collected for mobile phone message research. The second one is UtkMl’s Twitter Spam Detection Competition (UtkMl’s Twitter)

Table:1 The statistics of two datasets.

| | SMS Spam Collection v.1 | UtkMl’s Twitter |
|---|---|---|
| Spam | 747 | 5815 |
| Ham | 4827 | 6153 |
| Total | 5574 | 11968 |

**Confusion Matrix:**

It is the most commonly used evaluation metrics in predictive analysis mainly because it is very easy to understand and it can be used to compute other essential metrics such as accuracy, recall, precision, etc. It is an NxN matrix that describes the overall performance of a model when used on some dataset, where N is the number of class labels in the classification problem.

Table :2 The confusion matrix.

$$Accuracy = \frac{TP + FN}{N}$$

| | Predicted Spam | Predicted Ham |
|---|---|---|
| Actual Spam | True Positive (TP) | False Negative (FN) |
| Actual Ham | False Positive (FP) | True Negative (TN) |

In order to evaluate the performance of the proposed modified spam Transformer model, some metrics such as accuracy, precision, recall, and F1-Score are used in the experiments. All these metrics are calculated based on the confusion matrix. As is mentioned in the previous section, the spam messages in the SMS Spam Collection v.1 dataset are significantly less than the ham messages, which means that the dataset is unbalanced. Therefore, the accuracy is not sufficient as a measurement to evaluate the performance of the proposed model, and the F1-Score is employed in the experiments. The accuracy, precision, recall, and F1-Score is defined as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = 2 \times \frac{precision+Recall}{Precision + Recall}$$

| Classifiers | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Logistic Regression | 81.51% | 0.8441 | 0.7615 | 0.8007 |
| Naïve Bayes | 83.21% | 0.8316 | 0.8221 | 0.8269 |
| Random Forests | 79.28% | 0.8449 | 0.7044 | 0.7683 |
| SVM | 82.68% | 0.8681 | 0.7604 | 0.8107 |
| LSTM | 81.04% | 0.8594 | 0.7307 | 0.7898 |
| CNN-LSTM [22] | 79.45% | 0.8182 | 0.7438 | 0.7792 |
| Spam Transformer | **87.06%** | **0.8746** | **0.8576** | **0.8660** |

Table: 3 Results Of Different Classifiers for sms spam

**Service Provider:**

A valid username and password are required for the Service Provider to access this module. Once he successfully logs on, he will be able to do tasks like Take a look at the Train and Test and SMS Message Data Sets, You may see the results of the trained and tested accuracy in a bar chart. You can also see the types of SMS messages that are predicted, the ratio of those types to total messages, and data sets that are predicted for SMS messages that can be downloaded. Check the Type Ratio of Your SMS Messages, See Who Is Remotely Accessible.

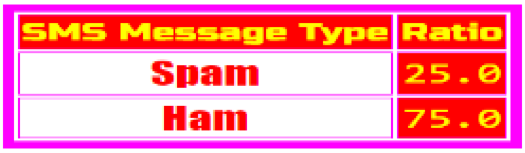
### View and Authorize Users

The admin can get a complete rundown of all registered users in this section. Here, the administrator may see the user's information (name, email, and address) and grant them access.

### Remote User

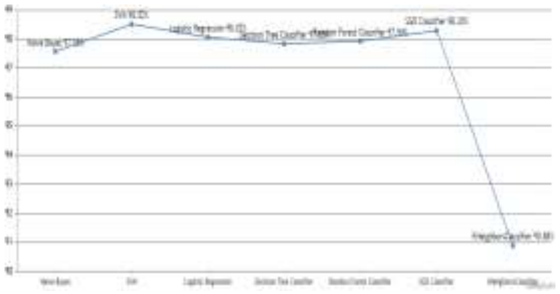
There are an equal number of users in this module. Before doing any actions, the user is required to register. The user's information will be entered into the database after they register. He will be prompted to provide his authorised user name and password upon successful registration. User may do actions such as seeing their profile, predicting the kind of SMS message, and more after successful login.

## RESULT ANALYSIS

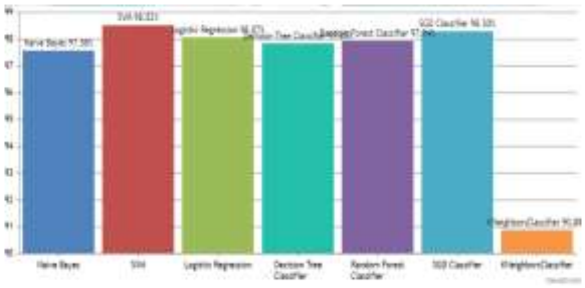


| SMS Message Type | Ratio |
|---|---|
| Spam | 25.0 |
| Ham | 75.0 |

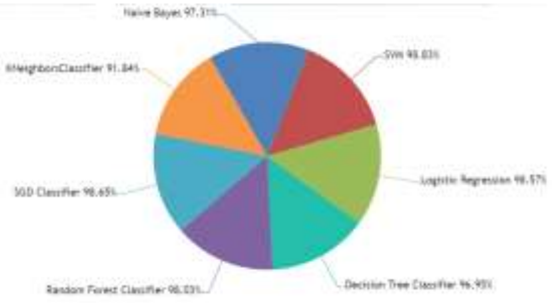
Prediction Ratio Details



Line Chart Prediction Results



Bar Chart Prediction Results



Pie Chart Prediction Results

## CONCLUSION

In conclusion, the development of transformer-based models for detecting SMS spam presents a promising avenue for enhancing the security and reliability of SMS communication platforms. Through the exploration of transformer architectures such as BERT, GPT, and XLNet, researchers have demonstrated the effectiveness of these models in capturing contextual information and linguistic patterns within SMS messages. By leveraging attention mechanisms and self-attention mechanisms, transformer-based models can effectively discernsubtle differences between spam and legitimate messages, achieving high accuracy and robustness in spam detection tasks. Additionally, the integration of transformer-based embeddings and multimodal approaches offers exciting opportunities for further improving the performance of SMS spam detection systems, enabling more comprehensive analysis of SMS messages and enhancing detection capabilities.Looking ahead, future exploration in this area ought to zero in on tending to difficulties such as domain adaptation, multilingualism, and scalability to real-world deployment. Furthermore, exploring the integration of reinforcement learning techniques and domain-specific knowledge into transformer-based models can further enhance their adaptability and effectiveness in combating emerging spam threats. By fostering interdisciplinary collaboration and leveraging advances in natural language processing and machine learning, the development of transformer-based models for detecting SMS spam holds the potential to altogether upgrade the security and trustworthiness of SMS communication platforms, ensuring users' privacy and safety in digital communication environments.

## FUTURE ENHANCEMENT

The future of developing transformer-based models for detecting SMS spam holds tremendous potential for advancing the security and reliability of SMS communication platforms. One promising direction is the exploration of multimodal transformer architectures capable of integrating diverse data modalities, such as text, images, and metadata, to enhance the accuracy and robustness of spam detection. By leveraging multimodal information, these models can capture additional contextual cues and semantic relationships, enabling more comprehensive analysis of SMS messages and improving detection performance. Furthermore, the integration of reinforcement learning techniques into transformer-based models offers exciting opportunities for dynamic adaptation and optimization of spam detection strategies. By continuously learning from user feedback and evolving spam patterns, reinforcement learning-based transformer models can adapt their detection policies in real-time, thereby enhancing their effectiveness in combating emerging spam threats and ensuring timely mitigation.Additionally, the future of transformer-based models for SMS spam detection lies in their application in diverse linguistic contexts and cultural settings. Multilingual transformer architectures, capable of processing and understanding SMS messages in multiple languages, hold promise for addressing the global nature of spam and enabling effective detection across linguistic barriers. Moreover, the development of domain-specific transformer models trained on domain-specific SMS datasets, such as financial transactions or healthcare communications, can further improve the accuracy and relevance of spam detection in specialized contexts. By tailoring transformer-based models to specific linguistic and domain-specific requirements, researchers can unlock new avenues for enhancing the security and trustworthiness of SMS communication platforms, ensuring users' privacy and safety in diverse communication environments.

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