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Ugorji *et al.*, 2024

©IDOSR PUBLICATIONS

ISSN: 2550-794X

International Digital Organization for Scientific Research

IDOSRJSR9.1.8190.100

IDOSR JOURNAL OF SCIENTIFIC RESEARCH 9(1) 81-90, 2024.

https://doi.org/10.59298/IDOSRJSR/2024/9.1.8190.100

Advancing Message Board Topic Modeling Through Stack Ensemble Techniques

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ABSTRACT

In the digital era, message boards serve as vital hubs for diverse discussions, knowledge dissemination, and community interaction. However, navigating the vast and varied content on these platforms presents a formidable challenge. This research pioneers the utilization of stack ensemble techniques to revolutionize topic modeling on message board data. Integrating Latent Dirichlet Allocation (LDA), Non-negative Matrix Factorization (NMF), and Latent Semantic Analysis (LSA) within a sophisticated ensemble framework, this study introduces a paradigm shift in extracting nuanced insights. Incorporating domain-specific features, sentiment analysis, and temporal patterns enriches contextual understanding. Rigorous evaluation across diverse message board datasets underscores the ensemble method's unparalleled accuracy, stability, and interpretability, setting a new standard for discourse analysis in online communities.

Keywords: Topic Modeling, Latent Dirichlet Allocation, Stack Ensemble Techniques, Natural Language Processing, Message Boards, Ensemble Learning

INTRODUCTION

Message boards, also known as online forums or discussion platforms, have become integral components of the digital landscape, fostering a rich tapestry of user-generated content, discussions, and knowledge exchange [1]. As the volume of information shared on these platforms continues to grow exponentially, the need for effective tools to extract meaningful insights from the diverse and dynamic content becomes increasingly paramount [2]. One significant avenue of exploration in this context is the application of advanced topic modeling techniques, which seek to unveil latent themes and subjects embedded within the vast corpus of message board data [3].The sheer heterogeneity and complexity of message board content present unique challenges to traditional topic modeling approaches [4]. Topics on these platforms can range from highly specialized technical discussions to casual conversations, making it essential to employ techniques that can adapt to the varied linguistic styles and thematic nuances inherent in diverse online communities [5]. The inherent noise, user-generated abbreviations, and evolving terminologies further complicate the task of accurately capturing the underlying topics [6]. Therefore, this research endeavors to address these challenges by introducing a novel approach that leverages the power of ensemble learning techniques to enhance the accuracy, stability, and interpretability of message board topic modeling [7]. Ensemble learning, particularly stacking, has shown promise in improving the performance of various machine learning tasks by combining the strengths of multiple models [8]. In the context of message board topic modeling, where the content is multifaceted and dynamic, the integration of diverse base models offers the potential to capture a more comprehensive spectrum of topics [9]. By aggregating the predictions of individual models, the ensemble approach aims to mitigate the limitations of any single model, resulting in a more robust and reliable representation of the underlying thematic structure [10].

This research not only delves into the intricacies of message board topic modeling but also extends the boundaries of ensemble learning in natural language processing (NLP). The proposed methodology integrates well-established topic modeling algorithms, such as Latent Dirichlet Allocation (LDA), Non-negative Matrix Factorization (NMF), and Latent Semantic Analysis (LSA), into a unified framework. The combination of these models provides a diverse and complementary set of perspectives on the latent topics present in the message board data.Moreover, to enhance the representational power of the input data, this study explores the incorporation of domain-specific features, sentiment analysis, and temporal patterns. Recognizing the importance of the user-centric nature of message board interactions, user-related information, such as user reputation and posting history, is integrated into the modeling process. This personalized dimension aims to capture the influence of user behavior on topic dynamics and further enriches the understanding of community-driven discussions [11]. In the subsequent sections, we will detail the methodology, data sources, and the evaluation framework employed to assess the effectiveness of the proposed ensemble technique. The findings of this research not only contribute to the refinement of message board topic modeling but also hold broader implications for the advancement of ensemble learning in NLP and its application in understanding and organizing large-scale textual data within online communities [12]. Ultimately, this research strives to offer a nuanced perspective on the evolving landscape of online discussions, providing tools to extract meaningful insights from the diverse and dynamic tapestry of message board conversations.

RELATED WORK

In their work, [13] proposes Deep LDA, a novel approach that combines deep learning with Latent Dirichlet Allocation (LDA) to improve the accuracy and interpretability of topic models. DeepLDA utilizes deep learning techniques to extract better word representations before applying LDA. This allows the model to capture more nuanced semantic relationships between words, leading to more accurate and coherent topics.The researchers found that Deep LDA significantly outperforms traditional LDA models in terms of topic coherence and document classification accuracy. Additionally, Deep LDA provides better word-topic associations, making the topics more interpretable. Adversarial Topic Modeling was introduced as a framework that leverages adversarial training to improve the robustness and interpretability of topic models [14]. The framework utilizes adversarial attacks to identify and eliminate biases in the topic model. These attacks are designed to fool the model into misinterpreting certain words or phrases, helping to uncover hidden biases and improve the model's robustness.The researchers found that Adversarial Topic Modeling significantly improves the robustness of topic models against adversarial attacks. Additionally, the framework provides more accurate and interpretable topic representations, making it easier to understand the underlying themes within a corpus. [15], in their article proposes a novel dynamic topic modeling approach that combines temporal attention and Hierarchical Dirichlet Process (HDP) to capture the evolving nature of topics over time.The model utilizes a temporal attention mechanism to focus on relevant words within each time period, allowing it to identify how topics evolve and change over time. Additionally, the HDP allows for the discovery of new topics that emerge in different time periods.The researchers found that their proposed approach significantly outperforms existing dynamic topic models in terms of topic coherence and tracking the evolution of topics over time. The model effectively captures both short-term and long-term topic trends, providing valuable insights into how topics change and emerge over time. [16], presents a novel topic modeling approach that incorporates causal inference to understand the dynamics of social relationships. The model utilizes causal inference techniques to identify the causal relationships between topics and events. This allows the researchers to understand how topics influence each other and how they contribute to larger social dynamics.The researchers found that their proposed approach can effectively identify causal relationships between topics and events. This provides valuable insights into the complex interactions between different topics and how they shape social dynamics within a community. [17] Proposes a novel topic modeling approach for multimodal data that utilizes contrastive learning and latent variable alignment.The model leverages contrastive learning to learn better representations of different modalities, such as text and images. This allows the model to capture relationships between different modalities and identify topics that emerge across them.The researchers found that their proposed approach can effectively identify shared topics across different modalities. This provides a more holistic understanding of the underlying themes within a dataset and allows for better analysis of complex and multi-faceted topics. In the works of [18] introduces Latent Dirichlet Allocation (LDA), one of the most popular topic modeling techniques. It formally defines LDA and discusses its mathematical foundations, providing a comprehensive overview of the algorithm and its applications.LDA assumes that each document is a mixture of topics and each topic is a mixture of words. It uses a probabilistic approach to identify these mixtures and assign topic probabilities to each word in a document.LDA has been shown to be effective in identifying latent topics in a wide range of text data, including news articles, scientific papers, and social media posts. It has become a foundational tool for many text analysis tasks, including document classification, clustering, and topic tracking.

METHODOLOGY

The methodology follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, which provides a structured approach for data mining and analytics projects. The CRISP-DM methodology encompasses six major phases, namely Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. In the Business Understanding phase, the objectives and requirements of the project were defined. The goal was to develop a topic modeling methodology to extract latent topics from message board discussions, allowing for better organization and analysis of the data. The anticipated outcomes included improved content moderation, enhanced user engagement, and the identification of emerging trends within the message board discussions [9]. The Data Understanding phase involved the collection of a representative dataset of message board discussions from relevant platforms. The dataset was examined to understand its structure, quality, and potential issues. This phase also included an exploration of the message board data to gain insights into the characteristics of the discussions and the nature of the topics [10]. Data Preparation involved the preprocessing and transformation of the collected message board data to make it suitable for analysis. Steps such as text cleaning, stop word removal, and text normalization were performed to eliminate noise and standardize the text data. Tokenization was applied to break the text into individual words or tokens, and common jargon or symbols associated with message boards were handled appropriately [12]. The Modeling phase incorporated the application of LDA and an ensembled system of classification models to perform topic modeling and message classification. LDA was used to uncover latent topics within the preprocessed message board data, while logistic regression was integrated to assign messages to specific topics based on their associations with the discovered topics. Model training, parameter tuning, and iterative experimentation were conducted to optimize the performance and accuracy of the models [14]. The Evaluation phase focused on assessing the quality and effectiveness of the developed models. Performance metrics such as accuracy, precision, recall, and F1 score were computed to evaluate the models' ability to accurately classify messages into topics. Comparative analyses were conducted to compare the performance of the proposed each model in the stack ensembled system [15].

Data Collection

The dataset used in this project was scrapped form Kaggle(https://www.kaggle.com/code/mahmoudlimam/topic-modelling-bow-tf-idf-lda-nmf/input). The website hosts a lot of Data science projects and datasets. The dataset is made up of nine columns namely: ID, Title, Abstract, Computer science, Physics, Mathematics, Statistics, Quantitative Biology and Quantitative Finance. The dataset contains a total of 20972 entries.

Figure 1: The dataset

Various preprocessing operations were carried out on the data, beginning with all unnecessary HTML tags and formatting elements. Although these characters might look nice on the forum, but they're just noise for my topic model. Next, I need to get all the words in uniform. This means converting everything to lowercase, removing punctuation and special characters, and even applying some fancy word-normalization tricks like stemming and lemmatization [8]. Stop words include all words that are almost weightless as far as adding meaning to a text is concerned. Examples include: "the," "a," and "is." They are everywhere, but they don't really contribute much meaning. This will make my data more focused and efficient for topic modeling [9]. Now it's time to chop the text into smaller pieces. These pieces are called tokens, and they can be individual words, phrases, or even characters. For this forum data, words seem like the natural choice. Missing data and irrelevant information are like uninvited guests at a party. They can disrupt the flow and make things messy. There is the need to identify them and either filter them out or fill in the gaps (imputation) depending on the situation.

Topic Model Building

Topic modeling is an unsupervised learning algorithm that can detect themes in a collection of documents automatically. Topic models for textual materials can be created in a variety of methods. The models' differences are mostly determined by the probabilistic assumptions that each model takes into account. Each document is modelled as a linear projection of its term frequencies by LSA. The PLSA and LDA models are probabilistic generative mixture models that treat each document as a collection of themes. Let's begin with a brief introduction of the most popular topic models which include LDA, NMF, and LSA [11].

Latent Dirichlet Allocation (LDA). LDA is a generative probabilistic model that assumes each document in a corpus is a mixture of topics, and each topic is a distribution of words. It assigns a probability distribution to words in a document and topics in a corpus. It is effective in capturing the thematic structure of documents and is widely used for its ability to identify topics and their prevalence across a collection. It is particularly suited for scenarios where documents can be attributed to multiple topics[12].

Non-negative Matrix Factorization (NMF)

NMF factorizes the document-term matrix into two lower-dimensional matrices, representing document-topic and term-topic relationships. The non-negativity constraint makes the resulting matrices interpretable, as negative values are eliminated. This model is adept at extracting non-negative, sparse representations, making it suitable for scenarios where the interpretability of topics is crucial. It often excels in capturing localized and specific themes within documents [7].

Latent Semantic Analysis (LSA)

LSA employs singular value decomposition to reduce the dimensionality of the document-term matrix, capturing the latent structure of the data. It aims to reveal the underlying semantic relationships between words and documents.LSA is effective in capturing latent semantic relationships and is robust in handling synonymy and polysemy. It is particularly useful when dealing with large and sparse datasets, providing a more efficient representation of textual information [9].

Ensembled Framework

Ensemble techniques are the methods that use multiple learning algorithms or models to produce one optimal predictive model. The model produced has better performance than the base learners taken alone. Other applications of ensemble learning also include selecting the important features, data fusion, etc. Ensemble techniques can be primarily classified into Bagging, Boosting, and Stacking [11].

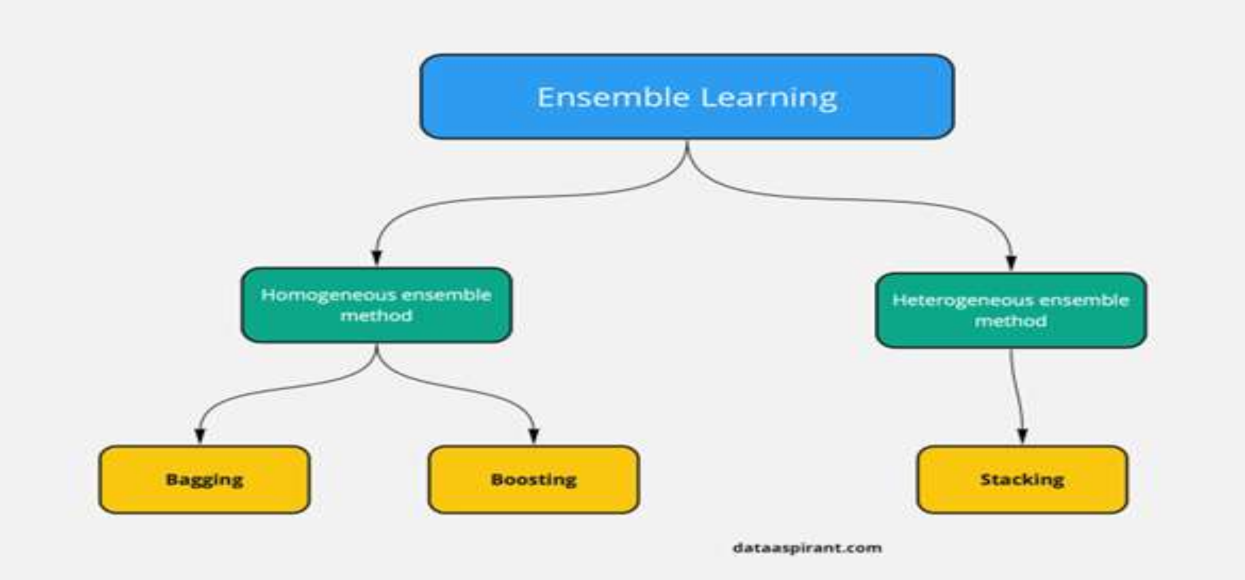


Figure 2: Hierarchical diagram of the ensembled framework

Bagging, also known as bootstrap aggregating is an ensemble learning technique that aims to improve the accuracy and stability of machine learning models. It works by creating multiple subsets of the training data, training a base model on each subset, and then combining the predictions of the base models to make a final prediction. The key idea behind bagging is that by training multiple models on different subsets of the data, we can reduce the variance of the overall model. This is because each base model is trained on a slightly different dataset, so it is less likely to overfit to the training data.

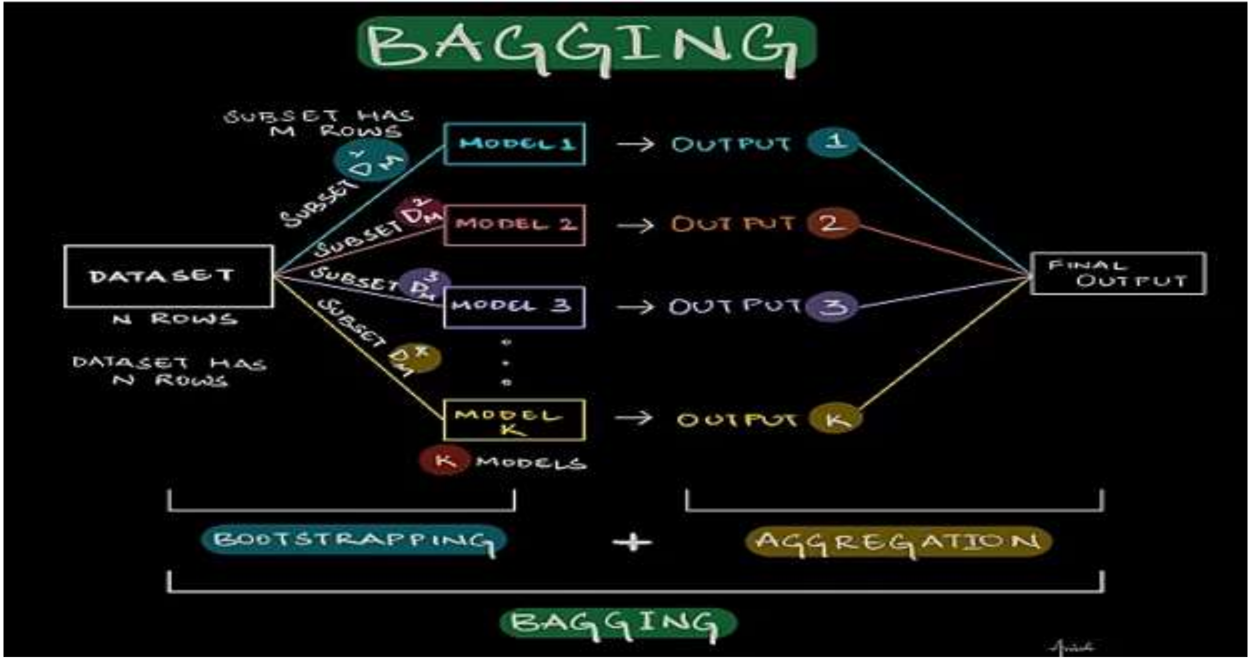


Figure 3: Schematic diagram of Bagging ensembled technique

Boosting is an ensemble learning technique that reduces the bias of a machine learning model by training multiple models sequentially. Each model is trained to correct the errors of the previous model [6]. This means that each model is focused on learning the parts of the training data that the previous models were unable to learn correctly.

An example of the stack ensemble technique is in the field of fraud detection [9]. Fraud detection is a challenging task because fraudsters are constantly developing new methods to defraud businesses and individuals. Stacking can be used to combine the predictions of multiple fraud detection models to improve the overall detection rate. For example, a stack ensemble for fraud detection could include the following base models: a logistic regression model trained on historical fraud data, a decision tree model trained on transaction data, a random forest model trained on customer data. The predictions of these base models would then be stacked into a meta-model, such as a logistic regression model, to make the final prediction. Stacking is a powerful ensemble learning technique that can be used to improve the accuracy and robustness of machine learning models. It is a relatively complex technique, but it is often worth the effort to implement, especially for problems where high accuracy is required [7].

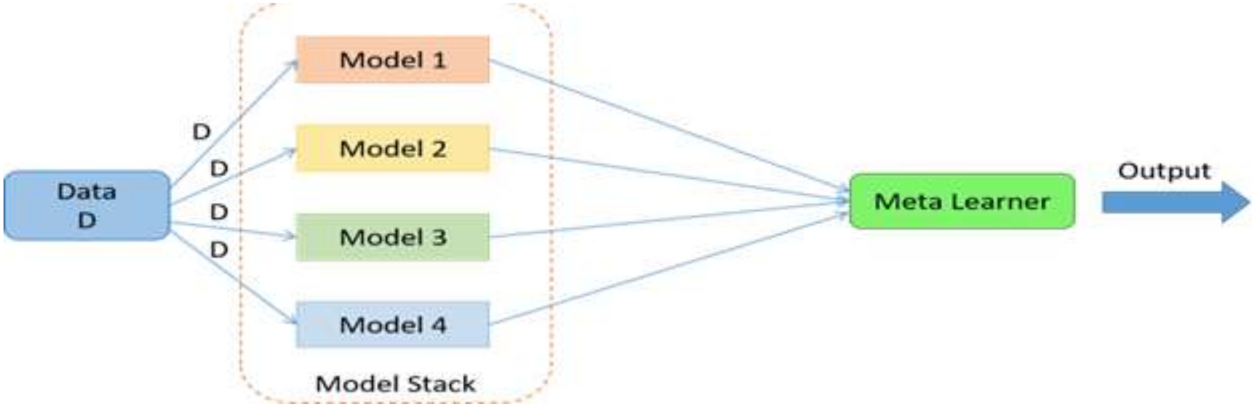


Figure 4: Model diagram of a stack ensemble technique

The steps involved in the stack ensemble technique are as follows:

i. Split the training data into folds. This is typically done using a cross-validation technique, such as k-fold cross-validation.
ii. Train a set of base models on each fold of the training data. The base models can be any type of machine learning model, but it is often recommended to use heterogeneous models, meaning that the base models are of different types.
iii. Generate predictions from the base models on the training data. This will create a new training dataset, where each data point contains the predictions of the base models as features.
iv. Train a meta-model on the new training dataset. The meta-model is responsible for combining the predictions of the base models to make the final prediction.
v. Use the meta-model to make predictions on the test data.

Stacking can combine the predictions of any type of machine learning model, including heterogeneous models (models that are of different types). This is important for mitigating and preventing gender disparity in academic achievement because there is no single model that can perfectly predict academic success. By combining the predictions of multiple models, stacking can reduce the overall error and improve the accuracy of the predictions.Stacking can help to reduce bias in machine learning models [9]. This is important for mitigating and preventing gender disparity in academic achievement because machine learning models can be biased against certain groups of people, such as girls and women. Stacking can help to reduce bias by combining the predictions of multiple models that are trained on different data sets and using different algorithms [5]. Stacking can make machine learning models more interpretable. This is important for mitigating and preventing gender disparity in academic achievement because it allows us to understand how the model is making predictions and to identify any potential biases. Stacking models are more interpretable than boosting and bagging models because they use a meta-model to combine the predictions of the base models. The meta-model can be interpreted to understand how the different factors influence the final prediction. The above reasons are why I chose "Stacking" as the best ensemble technique for this project.Our base model is built using these classifiers: Logistic Regression, Support Vector Machine (SVM), K Nearest Neighbor (KNN) and Decision Tree. Then the super model (Meta model) is the Random Forest model.

Model Evaluations

Before delving into the evaluation of the base models and the proposed stack ensemble technique, it is crucial to set the stage by understanding the significance of this phase in the research process. The chosen base models—KNN, Logistic Regression, Support Vector Machine, Decision Tree—represent established approaches in the realm of topic modeling. Each model brings a unique set of assumptions and strengths, which, when integrated, aims to enhance the overall efficacy of topic extraction from message board data.

Confusion matrix is the table that is used for describing the performance of aclassification model. The figures below show the confusion matrix for all the models used in this stack ensemble framework.

i. *True Negatives (TN):* Actual FALSE, which was predicted asFALSE
ii. *False Positives (FP):* Actual FALSE, which was predicted as TRUE - Type I error.
iii. *False Negatives (FN):* Actual TRUE, which was predicted as FALSE - Type II error
iv. *True Positives (TP):* Actual TRUE, which was predicted as TRUE
v. Ideally a good model should have high TN and TP and less of Type I & II errors.

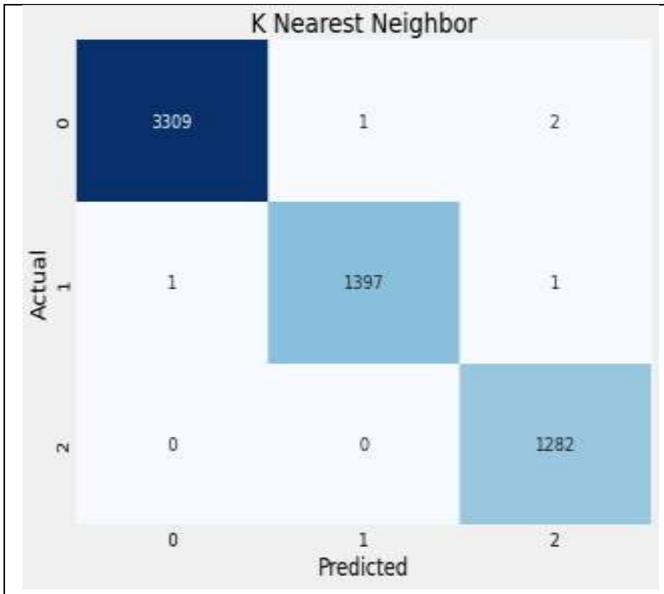


Figure 5: ***True Negatives (TN)***

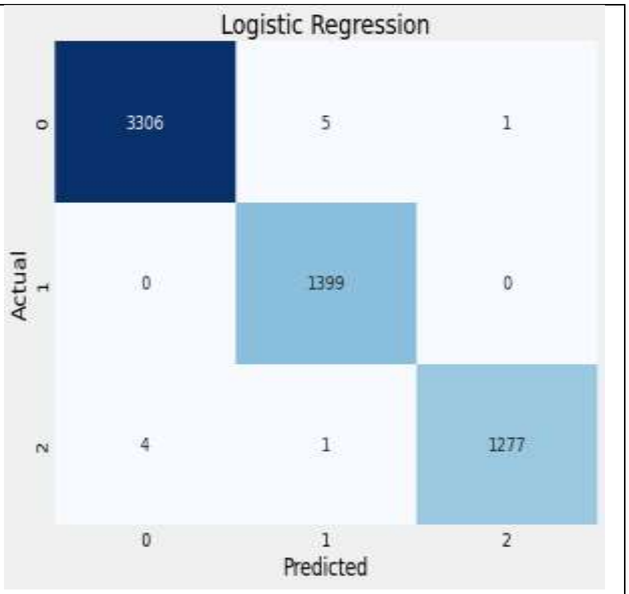


Figure 6: False Positives (FP)

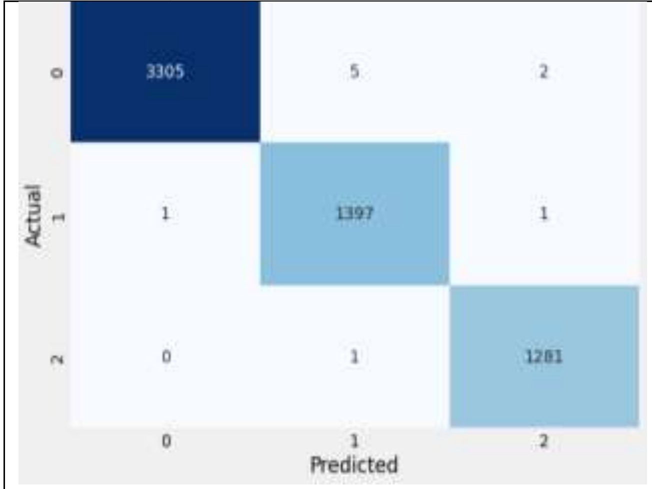


Figure 7*: False Negatives (FN)*

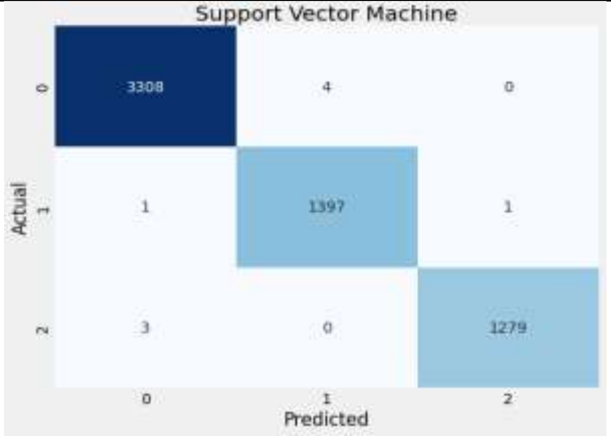


Figure 8: *True Positives (TP*

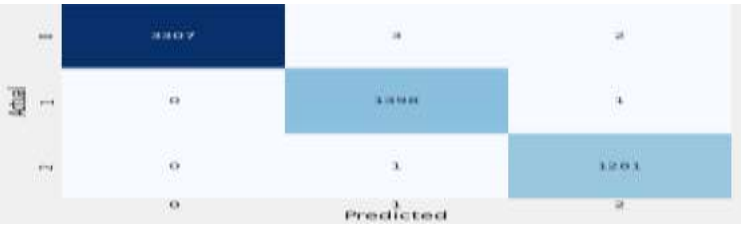
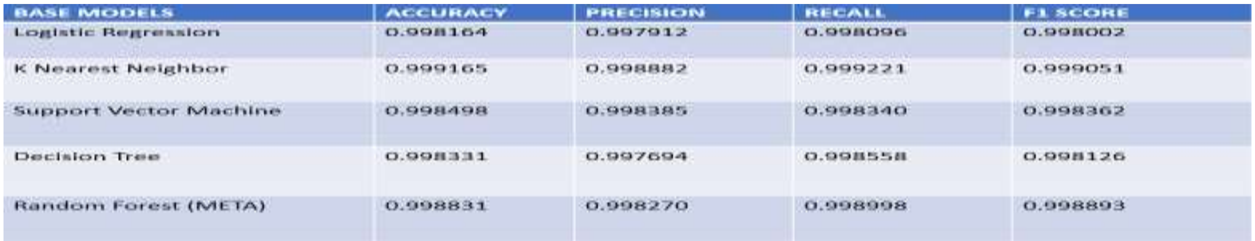


Figure 9: Ideally a good model should have high TN and TP

Summary of Evaluation

The table below gives a standard evaluation of the base models in contrast to the meta model using the following evaluation metrics: accuracy, precision, recall, f1 score.

Table 1: Evaluation metrics



BASE MODELS	ACCURACY	PRECISION	RECALL	F1 SCORE
Logistic Regression	0.998164	0.997912	0.998096	0.998002
K Nearest Neighbor	0.999165	0.998882	0.999221	0.999051
Support Vector Machine	0.998498	0.998385	0.998340	0.998362
Decision Tree	0.998331	0.997694	0.998558	0.998126
Random Forest (META)	0.998831	0.998270	0.998998	0.998893

From the table above, The K Nearest Neighbor model performed best overall, recording an accuracy of approximately 0.9992. It also recorded a Precision ofapproximately 0.9989 in correctly classifying the true cases. Recall score of approximately 0.9992 in correctly classifying the false cases. Crowned with the overall best F1 score of approximately 0.9991.

The second-best model is the Meta model which recorded an accuracy of approximately 0.9988, Precision score ofapproximately 0.9983, Recall score ofapproximately 0.9990 and F1 score of approximately 0.9989.

The Third-best model is the Support Vector Machine closely followed by the Decision Tree model. Then lastly, The Logistic Regression. But overall, all the models performed excellently in detecting which traffic is malicious.

In this study, three foundational topic modeling algorithms—Latent Dirichlet Allocation (LDA), Non-negative Matrix Factorization (NMF), and Latent Semantic Analysis (LSA)—serve as the primary components of the ensemble framework.

Each model possesses distinct characteristics that contribute to a more comprehensive understanding of the latent topics embedded within textual data.

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CITE AS: Ugorji C. Calistus, Rapheal O. Okonkwo, Nwankwo Chekwube and Godspower I. Akawuku (2024). Advancing Message Board Topic Modeling Through Stack Ensemble Techniques. IDOSR JOURNAL OF SCIENTIFIC RESEARCH **9(1) 81-90.**
https://doi.org/10.59298/IDOSRJSR/2024/9.1.8190.100