

Enhancing Email Intent Filtering Using Agentic AI-Based Model Selection

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Abstract

In the modern digital era, the rapid growth of email communication across organizations, educational institutions, business sectors, and government agencies has created significant challenges in managing and understanding large volumes of emails. The increasing dependency on email-based communication necessitates intelligent systems capable of automatically identifying the intent behind email content rather than performing only conventional classification. Traditional email filtering systems mainly rely on keyword-based techniques and conventional machine learning approaches, which often fail to understand contextual information such as email threads, user behavior, and implicit intent. In addition, these systems lack adaptive learning capabilities and do not support multi-step reasoning for handling complex and ambiguous email intentions.

To address these limitations, this research proposes an Agentic AI-based email intent filtering framework designed with autonomous agents, context-aware processing, and intelligent decision-making capabilities. The proposed multi-agent architecture performs specialized tasks including context analysis, intent inference, collaborative reasoning, and automated action execution. The workflow of the proposed system includes email ingestion and preprocessing, intent hypothesis generation, collaborative reasoning among agents, and final decision-making for intelligent email handling.

The proposed framework aims to improve the accuracy of detecting complex and ambiguous email intents while reducing manual effort in email management. Furthermore, the system provides a scalable and adaptive solution for modern digital communication environments by enabling intelligent and autonomous email management processes.

Keywords: Intent inference, collaborative reasoning, contextual information, email threads, Agentic AI, intent hypothesis generation.

1 Introduction

The rapid growth of digital communication technologies has significantly increased the role of electronic mail (email) as a primary communication medium in organizations and institutions. Business enterprises, educational institutions, healthcare organizations, and government sectors rely heavily on email for information exchange, decision-making, and workflow management. The increasing dependency on email communication has resulted in the generation of massive volumes of emails every day, creating challenges such as email overload, delayed responses, manual handling difficulties, and complexity in identifying the actual intent of messages. Efficient email management has therefore become an essential requirement for modern organizations.

Traditional email filtering and classification systems mainly focus on categorizing emails into spam and non-spam classes or into predefined folders using machine learning and natural language processing techniques [2]. Although these approaches improve basic email organization, they often fail to understand the contextual meaning, user intention, and semantic relationships within email content. Existing systems generally perform passive filtering and require manual intervention for prioritization, routing, and response management. As organizational communication becomes increasingly dynamic and complex, intelligent systems capable of reasoning and autonomous decision-making are required [1].

Recent advancements in Artificial Intelligence (AI), particularly Agentic AI, have introduced a new paradigm for intelligent communication management. Agentic AI systems are capable of autonomous reasoning, adaptive learning, contextual understanding, and dynamic decision-making. Unlike conventional AI models that only perform prediction or classification tasks, agentic systems can independently analyze situations, coordinate actions, and respond intelligently based on contextual requirements. This capability makes Agentic AI highly suitable for intent-driven email management systems.

The proposed work focuses on developing an Agentic AI-based email intent filtering framework that moves beyond traditional classification approaches toward intelligent intent-aware communication management. The framework employs a multi-agent architecture in which specialized agents collaboratively perform preprocessing, intent analysis, contextual reasoning, classification, and decision-making tasks. The system aims to identify the actual intent behind email communication, such as requests, complaints, approvals, scheduling, inquiries, or urgent actions, thereby enabling efficient prioritization and automated workflow handling.

The workflow of the proposed framework includes email preprocessing, feature extraction, natural language understanding, multi-agent reasoning, and adaptive decision mechanisms for intent classification. By integrating autonomous reasoning capabilities with intelligent filtering mechanisms, the proposed system enhances classification accuracy, reduces manual effort, improves response efficiency, and supports scalable email communication management. The framework can be effectively applied in enterprise communication systems, customer support environments, educational institutions, healthcare organizations, and other domains requiring intelligent email handling and automated decision support.

2 Literature Review

Emmanuel Gbenga Dada [1] explains about the machine learning methods used to successfully detect and filter spam emails. The review compares the strengths & drawbacks of existing machine learning approaches. DivyaSree et al [2] presents an intelligent email filtering system that leverages Natural Language Processing and Machine Learning to categorize email effectively. Mithili Devi et al [3] compares the efficiency of Random Forest, Naïve Bayes and SVM machine learning algorithms by the use of evaluation metrics in the detection of spam. A. Sesha Rao [4] et al presents the four layer perception network models for automatic email classification performance is enhanced with the use of Artificial Neural Network. Even Eilertsen [5] et al introduces an intent type taxonomy using machine learning to classify emails into different categories to generate active threat information publicly available datasets are used and the results demonstrate that existing LLMs are capable of detecting and classifying phishing emails. Kai Shu et al [6] developed an end to end robust deep neural network model for email intent identification that leverages both the clean and noisy weak data. The deep experiments on different intent detection tasks shows the approach is effectively leverage the weak data to improve the intent detection in email. Zaid Alibadi et al [7] produce results using three different types of embedding, contextual word embedding and sentence embedding achieved higher accuracy by using embeddings. Rahul Kavi et al [8] study the problem of intent classification using language models and large language models. Open source datasets are used from various domains like banking, travel, small talk etc. M. Sappelli et al [9] proposed a taxonomy of tasks that are conveyed through email messages. Two email datasets are annotated and evaluated the validity of the dimensions in that taxonomy. The proposed priority based categorization supports knowledge workers against email overload. Ramya Atchuta et al [10] proposes an intelligent email management and automation system using Agentic AI and the results show that the integrated system boosts productivity sustains the stable email quantity and shows the success of Agentic AI in day to day email management system. C.T.M. Pravven Kumar et al [11] compares the conventional spam filters with advanced filter techniques. This method supports the proper visualization by providing the dashboard, self directed and definable operations.

3 Limitations of Traditional Email Filtering Systems

Conventional email filtering systems primarily classify emails into spam and non-spam categories and lack a deeper understanding of user intent and contextual meaning. Most traditional machine learning-based models perform only

basic text classification and do not possess intelligent reasoning capabilities. As a result, these systems fail to interpret the semantic context and communication purpose behind emails effectively.

Existing email management approaches require considerable manual intervention for sorting, prioritizing, and handling emails. These systems are unable to dynamically adapt to continuously changing communication patterns and user behavior. Furthermore, conventional models struggle to identify complex intents such as complaints, scheduling requests, urgent actions, approvals, and customer inquiries, thereby reducing the effectiveness of communication management.

The rapid increase in organizational email traffic has created significant challenges including email overload, delayed responses, reduced productivity, and inefficient communication workflows. Although recent machine learning and natural language processing techniques improve classification performance, they mainly focus on text-based categorization rather than intelligent intent-driven communication management.

In addition, existing filtering frameworks lack autonomous decision-making, contextual reasoning, and adaptive learning mechanisms. Traditional systems are not suitable for efficiently managing large-scale and real-time enterprise email communication environments. They also provide limited support for workflow automation and experience difficulty in processing informal language and multi-context conversations.

Scalability remains another major concern while handling high volumes of organizational emails. Overall, current email filtering approaches do not support multi-agent reasoning and advanced intelligent mechanisms required for efficient email understanding, autonomous prioritization, and intelligent communication management. These limitations highlight the need for an Agentic AI-based intent-aware email filtering framework capable of autonomous reasoning, adaptive learning, and scalable email management.

4 Need for Intelligent and Adaptive Filtering Mechanisms

Traditional email filtering systems mainly focus on spam and non-spam classification using conventional machine learning and text-based classification techniques. In the traditional approach, the workflow includes email collection, preprocessing, feature extraction, and classification. These systems generally employ static rule-based mechanisms or supervised learning approaches for filtering emails. The classification process is primarily based on predefined keywords, frequency analysis, and existing communication patterns. However, contextual understanding and semantic interpretation are not effectively incorporated into the filtering process.

The traditional model used in this work is the Naïve Bayes classifier. Naïve Bayes is a probabilistic machine learning algorithm based on Bayes' theorem and is widely used for email classification tasks. It performs email categorization using probability estimation and feature-based analysis. The model is mainly utilized for initial filtering and basic email classification because of its simplicity, faster execution, and lower computational complexity.

5. Research Gap in Intelligent Email Understanding

Despite its advantages, the traditional approach has several limitations. Conventional email filtering models cannot dynamically adapt to changing communication behavior and user interaction patterns. They possess limited scalability in large-scale enterprise email environments and fail to identify complex intents such as urgent requests, scheduling, approvals, and complaints. Traditional systems mainly perform static classification and lack intelligent reasoning, contextual understanding, adaptive learning, and autonomous decision-making capabilities.

6. Agentic AI Based Email Intent Filtering System

To overcome these limitations, the proposed framework adopts an Agentic AI-based intent filtering approach. The framework employs an autonomous and intelligent multi-agent architecture for advanced email understanding and communication management. Multiple AI agents collaboratively perform tasks such as preprocessing, intent analysis,

contextual understanding, reasoning, decision-making, and classification. The proposed framework supports adaptive learning and dynamic response generation, enabling intelligent intent-driven communication management.

The Agentic AI framework improves email prioritization, workflow automation, real-time reasoning, and scalable email handling. It significantly reduces manual effort while improving communication efficiency in enterprise environments.

The proposed framework utilizes a hybrid multi-model approach that combines Naïve Bayes, Linear Support Vector Machine (Linear SVM), and Logistic Regression models.

- **Naïve Bayes** performs probabilistic email classification and is mainly used for initial filtering and feature-based categorization.
- **Linear SVM** performs high-dimensional text classification and helps in the accurate separation of email intent categories. It improves classification performance for difficult and complex email patterns.
- **Logistic Regression** is used for predictive intent classification. It estimates probability scores for various intent categories and enhances decision-making and classification accuracy.

The hybrid multi-model integration improves classification accuracy, contextual understanding, robustness, adaptive learning, and intelligent reasoning. Overall, the proposed Agentic AI-based framework enables scalable, efficient, and intelligent enterprise email management.

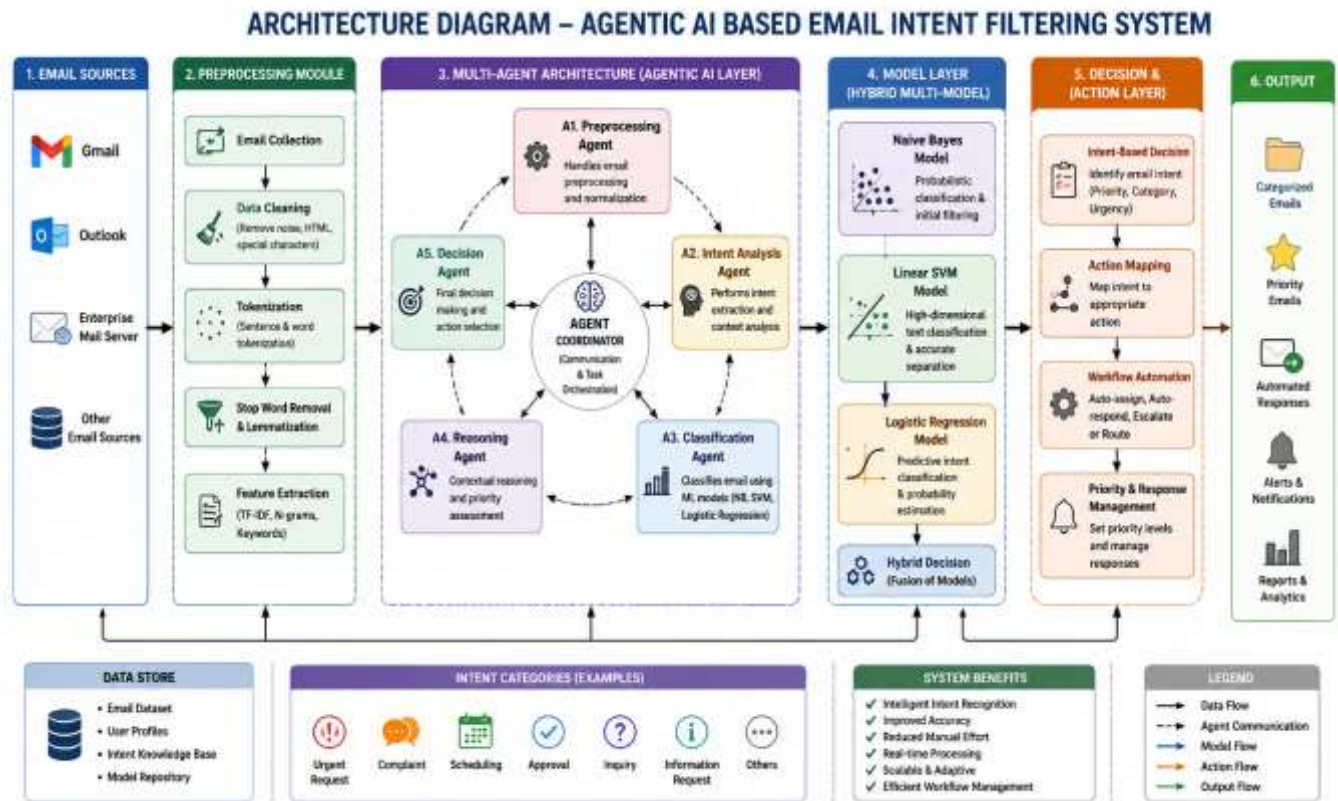


Fig 1: Architecture Diagram –Agentic AI Based Email Intent Filtering System[12]

7. Dataset Description

We use a dataset of email messages for training email intent filtering. It consists of around 5000 email entries, each labelled according to the intent mentioned in their content. All the data instances consist of two main features: The actual text within an email called email content and the type label of the email called intent category.

7.1 Intent Categories

Split into four main types, the data reflects what people often mean when they send emails. These categories show up regularly in everyday messages. Each group stands for a typical reason someone might write. Real-life usage shaped how these were sorted. Mail that shows someone is unhappy. Messages about problems people face as complaint, Emails requesting information or clarification as inquiry, Emails seeking technical or service-related assistance as support and Mail messages that share ideas, thoughts, or casual remarks as feedback.

7.2 Dataset Distribution

This creates a balance that eases training bias and increases the reliability of comparisons.

Complaint	~1250
Inquiry	~1250
Support	~1250
Feedback	~1250

7.3 Dataset Significance

An average of 5000 samples outperforms a dataset in terms of reliable evaluations. This enables the models to better learn patterns related to various email intents, and enhances the validity of using comparative analysis between traditional and agentic AI methods.

8. Implementation Details

Here we present tools, technologies and a detailed step-by-step process of how to implement the email intent filtering system using traditional AI and agenticAI.

8.1 Tools and Technologies

This was implemented using Python programming language for data processing and model development and Scikit-learn for implementing machine learning models, extraction of features and evaluation metrics.

8.2 Implementation Steps

The overall workflow of the system consists of the following stages:

8.2.1 Data Preprocessing

After the data acquisition was complete, we applied several preprocessing steps to prepare our dataset for machine learning models: Conversion of text to lowercase, Punctuation removal / special characters, Tokenisation of email text, Removal of stopwords, Feature extraction using TF-IDF vectorisation. The above steps would convert the email text to structures in a numerical format that can be used by our prediction model.

8.2.2 Feature Extraction

To convert textual data into numerical form, **Term Frequency–Inverse Document Frequency (TF-IDF)** vectorisation was used. This technique assigns weights to words based on their importance in the dataset, allowing the models to better understand the relevance of different terms in each email.

8.2.3 Model Training

Textual data has to be vectorised in order to convert it into numbers. This can be done by TF-IDF (Term Frequency–Inverse Document Frequency) vectorisation technique. TF-IDF is an important algorithm that weights words based on their importance in the dataset, so the models can identify which terms are more or less relevant among all those present in each email. This process is aimed at improving the efficiency in which machine learning algorithms are able to process and classify textual information.

In the model training phase, two types of treatment were applied. In traditional way, a single ML model i.e. Naive Bayes was trained on the data set which then used for predictions. This approach represents the conventional method of email intent classification using one fixed model.

On the other hand, agentic AI approach learning and evaluation using multiple learning models — Naive Bayes, Linear SVM and Logistic Regression. Through evaluation metrics, the agentic system automatically compared these models and chose the best one. This allows for the system to effectively and efficiently adapt itself as a dynamic way of selection among set of intents.

8.2.4 Evaluation

We evaluated the performance of both approaches with several conventional metrics such as Accuracy Score, Classification Report, and Confusion Matrix. The classification report gives specific statistics such as precision, recall and f1-score for each class, and visualizes how well a model has performed prediction-wise. These evaluation measures were used to compare the effectiveness of the traditional model and the Agentic AI approach in filtering and classifying email intents accurately.

9. Results and Discussion

This section presents the performance evaluation of the traditional model and the proposed agentic AI approach for email intent filtering. The analysis is supported by accuracy comparisons, classification reports, and confusion matrix interpretations, along with graphical representations included in the paper.

9.1 Model Performance Comparison

Fig 2 shows the performance of the various machine learning models in our agentic framework. But, we can see from the graph that Naive Bayes and Logistic Regression has an accuracy of 0.0 while Linear SVM got an 0.1667 accuracy. This shows that Linear SVM outperforms the other models for this particular dataset. The results show that not all models achieve high performance and selecting the optimal model is required to obtain better predictive power. Comparing the best models for each category, we find that Linear SVM is once again the winning model – and indeed this is what the agentic system selects as contextually optimal based on these comparisons.

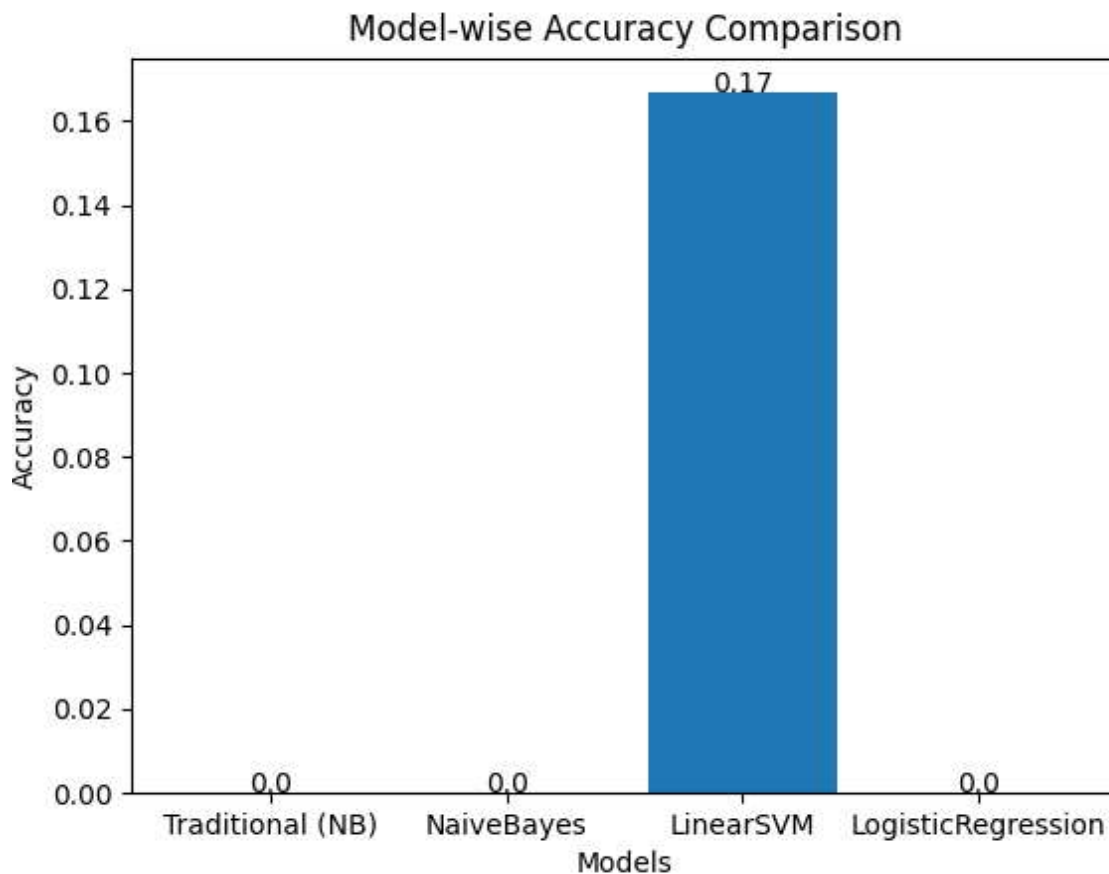


Fig 2 : Performance of various learning models

9.2 Traditional vs Agentic AI Performance

The overall comparison between the traditional approach and the agentic AI approach is shown in Fig 3. The traditional model achieved an accuracy of 0.0, whereas the agentic AI approach achieved an accuracy of 0.1667. This improvement highlights the effectiveness of the agentic system in dynamically selecting the most suitable model. Unlike the traditional approach, which relies on a single fixed model, the agentic approach evaluates multiple models and adapts its decision based on performance, resulting in better outcomes.

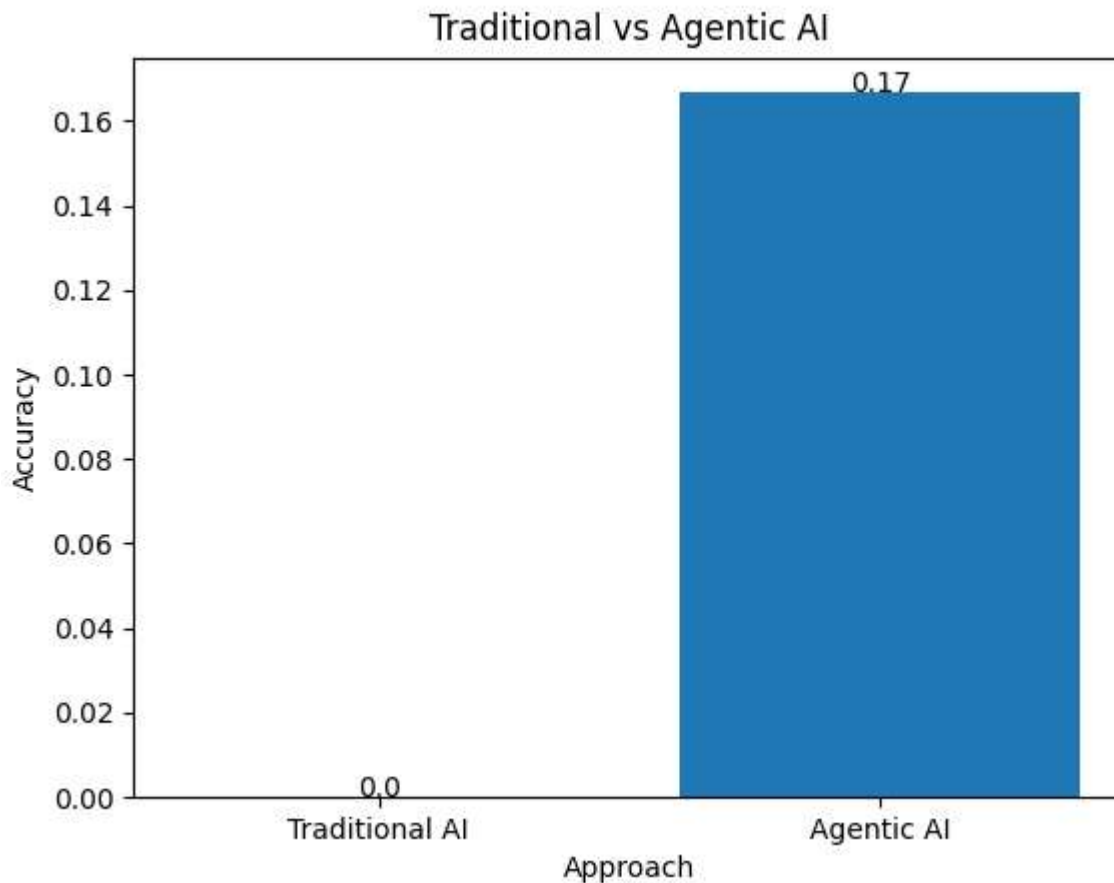


Fig 3 : Comparison between tradition AI and Agentic AI

9.3 Traditional Model Analysis

The confusion matrix of the traditional model is presented in Fig 4. The matrix reveals that most predictions are concentrated in a single class, specifically the “Feedback” category. There are no correct predictions along the diagonal, indicating that the model fails to correctly classify any of the email intents. This behaviour reflects a strong class bias and an inability to learn meaningful patterns from the data. As a result, the model achieves zero accuracy, demonstrating poor generalisation and ineffective learning.

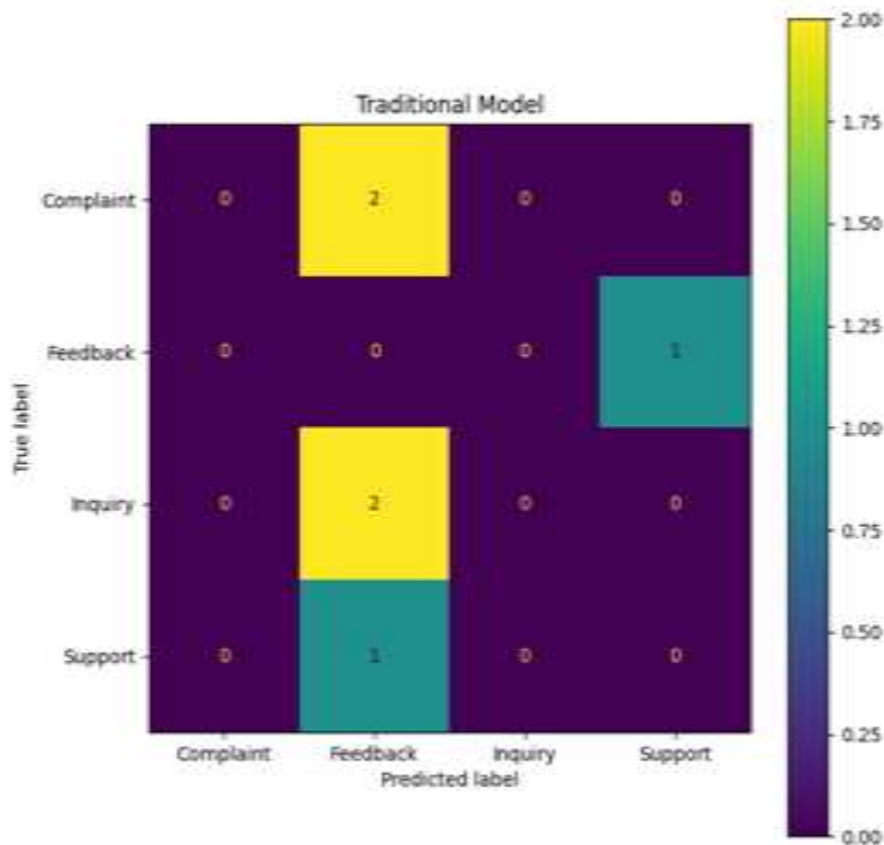


Fig 4 : Confusion matrix of Traditional Model

9.4 Agentic Model Analysis (Best Model: Linear SVM)

The confusion matrix of the agentic model, specifically the Linear SVM model selected by the agent, is shown in Fig 5. Unlike the traditional model, the predictions are more evenly distributed across different classes. The matrix also shows that at least one category, particularly “Support,” is correctly classified. This indicates that the model has learned some meaningful patterns from the data. The reduction in class bias and the presence of correct predictions demonstrate improved classification behaviour and better learning capability compared to the traditional model.

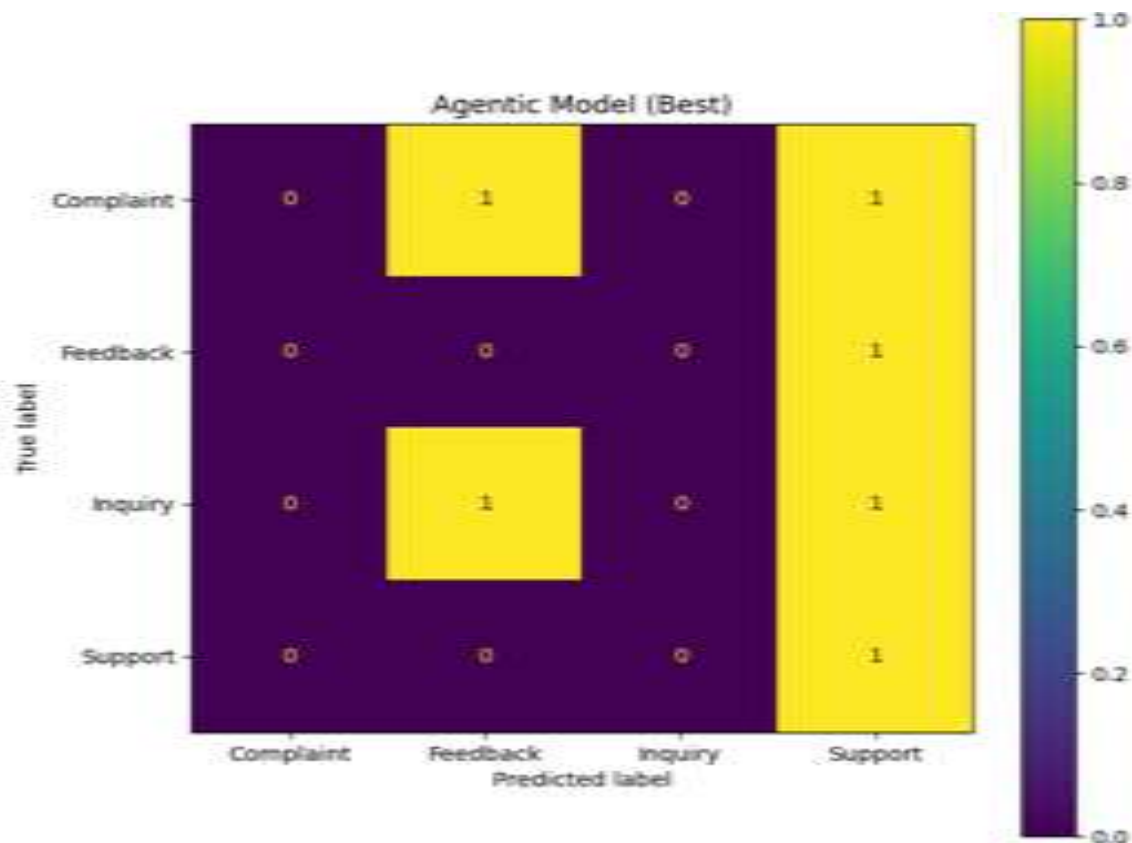


Fig 5 : Confusion Matrix of Agentic Model

9.5 Classification Report Analysis

The classification report further supports the observations from the confusion matrices. The traditional model shows zero precision, recall, and F1-score across all classes, confirming its complete failure in classification. In contrast, the agentic model achieves an overall accuracy of 0.17. Notably, the “Support” category shows a precision of 0.25, a recall of 1.00, and an F1-score of 0.40, indicating that the model is capable of correctly identifying certain classes. Although the overall performance is modest, it is significantly better than the traditional model.

The results clearly demonstrate that the agentic AI approach outperforms the traditional model in email intent filtering. The primary reason for this improvement is the ability of the agentic system to evaluate multiple models and select the best-performing one. While the traditional model is limited by its dependence on a single algorithm, the agentic approach adapts to the data and leverages the strengths of different models. The selection of Linear SVM, which performs better than other models, highlights the importance of dynamic model selection in improving classification performance.

The experimental results clearly indicate that the agentic AI approach performs better than the traditional model due to its ability to dynamically evaluate and select the most suitable model. Unlike the traditional approach, which relies on a single predefined algorithm, the agentic system explores multiple models and chooses the one that performs best on the dataset.

In this study, Linear SVM was identified as the optimal model, achieving higher accuracy compared to other models. This highlights the importance of model selection, as different algorithms exhibit varying performance on the same dataset. The adaptability of the agentic system allows it to respond effectively to the characteristics of the data, resulting in improved performance.

The use of a dataset containing over 5000 samples enhances the reliability of the results by enabling the models to learn more representative patterns. This contributes to better generalisation and a more realistic evaluation of performance.

10. Advantages of Agentic AI

The agentic AI approach offers several advantages over traditional machine learning methods in the context of email intent filtering. One of the primary benefits is automatic model selection, where the system evaluates multiple models and selects the best-performing one without human intervention. This ensures optimal performance and reduces the effort required for manual tuning.

Another significant advantage is the reduction of bias. Traditional models often exhibit bias toward specific classes, leading to poor classification results. In contrast, the agentic approach selects models that provide more balanced predictions across all categories, thereby improving overall performance.

Agentic AI systems also demonstrate better adaptability, as they can adjust their behaviour based on the performance of different models. This makes them more effective in handling diverse and complex datasets. Additionally, by leveraging multiple models and selecting the most suitable one, agentic AI improves learning performance, resulting in more accurate and reliable predictions.

Conclusion

This study presented a comparative analysis of traditional machine learning and an agentic AI approach for email intent filtering. The traditional method, which relies on a single predefined model, was found to have limitations in terms of adaptability and performance. In contrast, the proposed agentic AI system demonstrated the ability to dynamically evaluate multiple models and select the most suitable one based on performance metrics.

Experimental results showed that the agentic approach successfully identified Linear Support Vector Machine (Linear SVM) as the best-performing model, leading to improved accuracy and more balanced predictions compared to the traditional model. This highlights the effectiveness of automated model selection in enhancing classification performance.

Furthermore, the use of a larger dataset contributed to more reliable and realistic evaluation, enabling the models to learn meaningful patterns from email data. The findings confirm that agentic AI systems offer significant advantages in terms of adaptability, reduced bias, and improved learning capability. The proposed approach demonstrates that agentic AI is a more efficient and flexible solution for email intent filtering compared to traditional methods. Future work can focus on integrating advanced techniques such as deep learning and contextual embeddings to further improve performance and scalability in real-world applications.

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