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Inbox Ai – Personalized Email Generator with Tone Selection

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Abstract- Writing emails with correct tone is a common challenge for students, professionals and businesses. Many times the message is correct, but the tone does not match the context — resulting in misunderstandings, poor communication or unprofessional impact. Hence there is a need for a system that can automatically generate a well-structured email and adjust the tone according to the requirement. In this paper we propose a Personalized Email Generator with Tone Selection, which uses AI/NLP models to convert raw user input (idea/points) into a complete professional email. The system provides multiple tone options such as Formal, Friendly, Professional, Casual, Direct, and Promotional, and instantly rewrites the text accordingly. This helps users generate consistent, context-correct communication without manual editing or writing skills. The system can be deployed as a web app, extension or integrated tool for day-to-day email writing.

Keywords: NLP, Personalized Emails, Tone Classification, Text Generation, AI Writing, Email Automation, Communication Enhancement, Content Rewriting.

I. INTRODUCTION

In today's digital communication era, email has become one of the most widely used formal mediums of information exchange across education, corporate and professional domains. However, the biggest challenge is not writing emails — but writing them in the right tone according to the situation. A message written with wrong tone can lead to misunderstanding, unprofessional impression or communication failures. For example, a job application email must sound formal, a marketing email should sound persuasive, a feedback email should sound respectful, and a friendly message should sound casual and warm. Therefore, tone of an email is equally important as the actual content of the email.

Due to this, users — especially students, fresh professionals and non-native English speakers — struggle to frame proper emails and often depend on templates. But templates are fixed and cannot adapt to different purposes. Hence arises the need of an intelligent system that can dynamically generate personalized emails and automatically change the tone as per requirement. Cloud based writing tools exist, but stable internet and login dependency can be a problem for many users. Therefore, in this paper we propose a Personalized Email Generator with Tone Selection that can produce context-correct emails instantly, based on user input points, tone selection and minimal user effort, making communication smarter, faster and more effective.

II. RELATED WORKS

Existing AI writing assistants mainly focus on grammar correction, template suggestions or autocomplete writing. Tools like Grammarly, Quill Bot and other cloud based writing platforms can help in sentence rephrasing, but they do not generate complete personalized emails based on minimal input. Also, most of these tools do not allow users to select a specific tone and then convert the same input into multiple tone styles. Few studies in NLP have used transformer based models to perform tone transfer between formal and informal text [1], but these systems are still limited to short sentences. Research works have explored style transfer and sentiment control using LSTM based networks [2], however they lack structural understanding needed to generate complete emails.

Recent development of large language models (LLMs) and transformer models like GPT and T5 [3] have shown high performance in text generation and tone control tasks, proving that advanced NLP models can understand context and rewrite content while preserving meaning. Some mail clients have introduced short AI “Smart Reply” features [4], but they generate only one-line responses and not full emails. Studies on AI based content personalization [5] indicate that tone-based rewriting can improve communication effectiveness in professional environments. Therefore, based on this previous research, our system leverages tone-based text generation and applies it specifically for email generation, producing complete structured emails with selectable tone styles such as Formal, Casual, Professional, Friendly or Promotional.

Further, some commercial email tools support auto-complete and predictive suggestions inside email platforms (like Gmail Smart Compose) which uses sequence prediction models trained on massive email corpora [6]. However, the limitation with those systems is that they only assist in typing faster, they do not transform user ideas into full-length emails with controlled tone. Research in controllable text generation [7] has also introduced the concept of attribute-based text editing (formal vs informal), but such work focuses mainly on literary style conversion and not practical structured business communication. Moreover, tone classification models [8] have been explored for sentiment detection (positive, negative, neutral), but limited work exists in the domain of “tone manipulation” specifically tailored for email writing context.

III. DATA SET

Our basic objective is to generate personalized emails with user-selected tones. To achieve this, we created a custom dataset that contains email texts written in multiple tones for the same context. For this work, we developed and refined a Tone-Variant Email Dataset using publicly available email samples and manually written data. The dataset consists of approximately 2400 email samples divided into six distinct tone categories — Formal, Professional, Friendly, Casual, Direct, and Promotional. Each email sample represents the same core message rewritten across different tones to help the model learn contextual tone adaptation. Every email entry includes fields such as Subject Line, Body Text, and Tone Label. The dataset was preprocessed by cleaning HTML tags, correcting grammatical errors, and normalizing text length. Finally, all data was tokenized and encoded into a structured CSV format, making it suitable for fine-tuning and tone classification tasks. Table 1 shows the distribution of samples across all six tone categories, while Figure 1 (if included) can represent a few examples of tone variations for the same input message.

Since our system focuses on tone–controlled email generation, each email message in the dataset was re–written manually into multiple tone variants while preserving the same meaning. This parallel structure helps the model learn how the same message can be expressed in multiple different tones with minimal semantic loss. The distribution of samples in Table 1 shows how the dataset is balanced across six tone categories, ensuring that the trained model does not become biased towards any specific tone.

Table I. This Table Presents the Baseline Performance Comparison Between Multiple Models Applied For Tone-Based Email Generation.

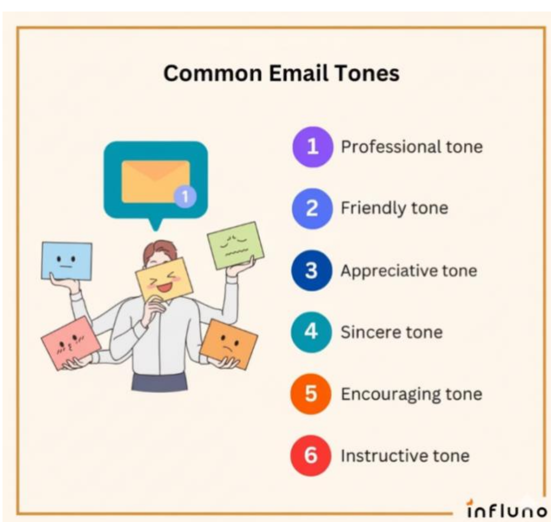
Tone Category	Number of Samples	Data Type Level	Description
Formal	500	High Formality	Official, Academic, Job related emails
Professional	400	Corporate Level	Office/Workplace communication
User Friendly	300	Human Centric	Warm, soft & friendly emails
Casual	380	Informal Level	Daily informal
Direct	260	To-the-point	Short, clear & fast communication
Promotional	320	Marketing Level	Sales pitch / Offer based communication
Total	2200+	-	Parallel Multi-tone dataset

Our dataset is specifically designed for tone–based email generation, which means each sample inside it is intentionally structured to capture not just the content of the message but also the emotional and professional "delivery style" of that same message. Instead of collecting random email texts from the internet, we developed a carefully refined dataset that contains multiple tone–variations of the same base message. This parallel format teaches the model how to rewrite a single idea into different tones without changing the meaning.

For example, the same email asking for internship confirmation is written in Formal tone, Professional tone, Friendly tone, Casual tone, Direct tone and also Promotional tone. This gives the model a strong comparative base to learn the subtle differences between tone, intention, politeness level and communication attitude.

The dataset is stored in machine–readable formats such as CSV and JSON, because these allow cleaner text extraction and easier processing during model training. Before training, every email sample goes through a set of preprocessing steps such as text cleaning, token normalization, stop–word adjustments and label encoding. These steps ensure that the model receives consistent and standardized text input.

This normalization is important, because raw email text collected from various sources contains extra spaces, signatures, unwanted punctuation and inconsistent formatting which would reduce model accuracy. By cleaning and preparing the text before training, we improve the general performance and reduce noise in the learning process.



This image clearly represents the concept that email communication is not limited to one fixed style. The same message can be expressed in different tones depending on the purpose. The person holding different face cards symbolizes "tone switching" — meaning the same idea can be delivered in various emotional or communication styles. This directly aligns with our project goal. In our Personalized Email Generator with Tone Selection, the user can write only the main points, and the system will automatically generate a complete email in a selected tone.

IV. USE OF LLM IN OUR PROJECT

In our project, the LLM (Large Language Model) is the main intelligence component that performs the end-to-end transformation of the content provided by the user. Normally, a user types short and unstructured points like "meeting tomorrow", "client confirmation", "project update", etc. These points are not in the form of a proper email. The LLM takes these raw points as input and converts them into a complete email body with proper sentence structure, grammar correction and paragraph formatting. This ability eliminates the need for the user to manually write long emails, because the LLM automatically understands what the user wants to convey and builds an actual professionally shaped message from it.

Another major use of LLM in our project is for tone personalization. In professional communication, tone plays a more important role than just grammar or spelling. The same content written in a Formal tone, Friendly tone or Casual tone will have different impact on the reader. The LLM learns tone patterns from massive language data and uses them in our system to rewrite the email in the exact tone selected by the user. This helps the model adapt sentence softness, politeness level, vocabulary selection and structure according to tone. For example, a Professional tone will be more direct and concise, while a Friendly tone will be soft, warm and easy-going.

LLM is also used in our project to preserve the semantic meaning of the original content. Many rewriting systems change the meaning when they paraphrase. But our LLM based approach focuses on generating a final email that expresses the same message intention, just in a different style. This ensures that even after tone transformation, the user's message does not lose its original purpose or clarity. This is very important because email communications in official environment should not distort information.

LLMs also help the system reduce manual dependence and improve productivity. Instead of searching templates online or manually editing email drafts, the user can simply enter points and select tone in one click. The LLM will finish the entire writing work for the user, saving time and effort. This is especially helpful for students, working professionals, freelancers and business teams who send multiple emails on daily basis.

Overall, the LLM is the core engine that enables our Personalized Email Generator to work like a smart assistant rather than a static template-based tool. It gives our system the capability to understand human context, generate meaningful content, maintain the meaning of user input, choose the right tone, and finally produce a polished, ready-to-send personalized email.

LLM also improves the scalability of our system. If we want to support more tones in the future (like sarcastic, excited, empathetic, persuasive, urgent), we do not need to build rules manually. Because an LLM already understands various forms of communication, we can simply train or fine-tune the model with new tone examples and the system will automatically learn how to generate emails in those new tone styles.

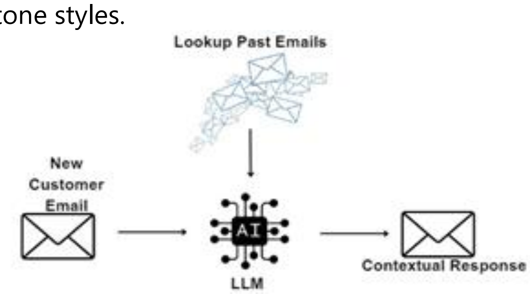


Fig. 1. Email Efficiency with LLMs.

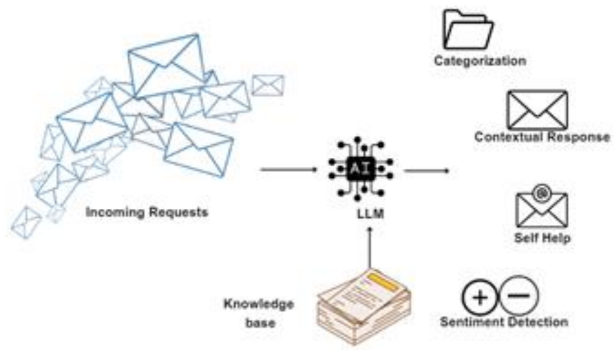


Fig. 2. Use Cases to Leverage LLMs in Customer Interactions.

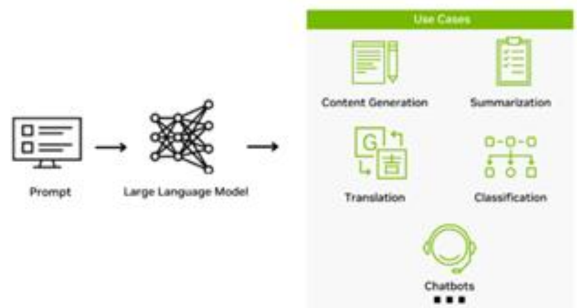


Fig. 3. LLMs for Enterprise Solutions.

Additionally, the LLM makes our project suitable for real-world usage, because emails are used in countless situations — job applications, client follow-ups, project updates, marketing messages, support replies, invitations and formal requests. With the power of an LLM, one system can automatically generate all types of emails without changing the core logic. This flexibility and adaptability makes our Personalized Email Generator not just a writing tool, but a smart tone-based communication system that can be used by almost every type of user in everyday life.

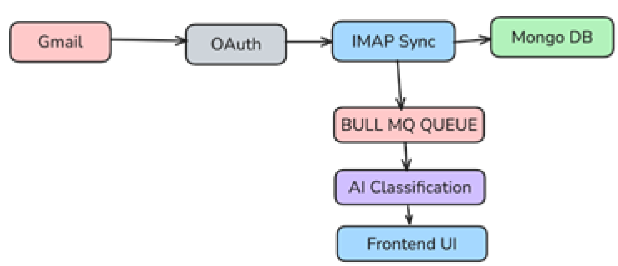


Fig. 4 Email Processing Workflow

Illustrates the end-to-end system architecture for email ingestion, processing, and intelligent classification within the proposed platform. The workflow begins with Gmail, which acts as the primary email source. User access to Gmail is securely authorized using OAuth, ensuring that sensitive credentials are never directly shared with the system. This authentication mechanism provides controlled and permission-based access to user mailboxes, maintaining privacy and security standards.

Once authentication is completed, the system performs IMAP synchronization, which enables real-time or periodic fetching of emails from the Gmail server. IMAP Sync ensures that incoming emails are consistently retrieved and updated without duplicating data. The synchronized emails are then stored in MongoDB, which serves as the primary data repository for raw and processed email content, allowing efficient storage, retrieval, and scalability.

To handle asynchronous and high-volume email processing, the system utilizes a message queue (BullMQ Queue). Emails fetched through IMAP Sync are pushed into the queue, decoupling email ingestion from processing. This queue-based architecture improves system reliability and performance by allowing background workers to process emails independently, preventing bottlenecks during peak loads.

The queued emails are then passed to the AI Classification module, where machine learning or natural language processing techniques are applied. This module analyses email content to classify messages based on predefined criteria such as intent, category, or tone. By performing classification asynchronously, the system ensures efficient utilization of computational resources while maintaining accuracy in email analysis.

Finally, the classified email data is delivered to the Frontend UI, where users can view organized and intelligently categorized emails. The frontend acts as the presentation layer, enabling users to interact with the processed data in a structured and user-friendly manner. Overall, the architecture shown in Figure 4 highlights a scalable, secure, and modular pipeline that integrates authentication, data synchronization, asynchronous processing, AI-based classification, and user interaction into a cohesive system.

V. METHODOLOGY

A. Input Collection

Input Collection is the first and most important step of our methodology because the user's entire intention and message requirement starts from this stage. In this step, the user does not have to write a full long email. Instead, the user only needs to type short points or rough sentences that describe what they want to communicate. This is more natural because most people think in "points" rather than in ready-made email sentences. For example, a student may write: "project submission reminder for teacher" or "internship confirmation follow-up". These points are enough for the system to understand what the final email should talk about.

In traditional email writing, the user wastes a lot of time creating sentence structure, thinking about how to write professionally and how to make proper paragraphs. But in our system, this writing burden is reduced. The user's job is only to enter the main content idea. The system intelligently expands these points into a full email later. This makes email writing extremely faster, especially for users who write multiple emails daily — like office employees, freelancers, students applying to internships, etc.

In this stage, the user will also select the tone of the email. Selecting tone is a major differentiating factor of our project. Because same message can be delivered in a formal manner or in a friendly manner depending on who the receiver is. So, tone selection becomes part of the input. For example, if the user selects "Formal", the final email will sound official. But if the user selects "Friendly", the same message will sound soft, warm and simple.

Input Collection also ensures personal control. The model does not randomly choose what to write — the model transforms exactly what the user wants to say. So this step ensures that the email is not just AI-generated text, but AI-generated text based on the real intention of the user. This keeps the meaning accurate.

Finally, this stage converts “user thoughts” into “structured input” for the system. After this stage the system has two things clearly:
(1) what to talk about → input content
(2) how to talk → selected tone

These two are then forwarded to the next steps for processing and generation.

B. NLP Preprocessing
After collecting the user’s input, the text is passed into the NLP Pre-processing stage. In this stage, the system cleans the raw text and converts it into a machine understandable format. A normal user may type short, incomplete sentences or bullet points without worrying about grammar or structure. NLP pre-processing ensures that the input is normalized, unnecessary elements are removed, and meaningful keywords are extracted. This helps the model get a clearer version of what the user is trying to say.

meaningful units (called tokens). These tokens help the system identify which words matter and how they connect with each other. For example, the system can identify whether the input is a request, an update, an apology, or a Next, the system performs Semantic Understanding. Semantic understanding means extracting the hidden meaning or intention behind the text. Two sentences may have different words but convey the same meaning — NLP helps detect that meaning instead of just matching words. This prevents confusion and helps the model rewrite the message without losing the original idea.

This preprocessing stage is very important before passing the content into the main LLM. If the raw input is sent directly without cleaning, the final generated email may contain errors or irrelevant information. By preprocessing the text first, we increase both accuracy and quality of the final generated email. So this step acts like a “filter” that refines the input and prepares it for tone-based generation in the later stages.

Text Cleaning and Tokenization are two major steps here. Text cleaning removes unwanted characters like extra spaces, random punctuation, informal symbols, or unnecessary words. Tokenization breaks the sentence into meaningful units (called tokens). These tokens help the system identify which words matter and how they connect with each other. For example, the system can identify whether the input is a request, an update, an apology, or a follow-up.

C. Tone Selection Module
Tone Selection Module is the most unique and defining part of our project. In this stage, the user chooses in which “tone” the final email should be written. Different tones represent different communication attitudes. For example, a Formal tone is strict, respectful and professional, while a Friendly tone is soft, warm and casual. In real-world communication, the same message cannot be sent to everyone using the same style. Talking to a teacher or HR demands a formal tone, but talking to a friend or teammate may need a friendly tone. This is exactly what this module handles — it decides “how” the email should sound.

Once the user selects a tone, the system loads the internal rules and patterns related to that tone. These rules are not fixed templates but “style indicators” learned by the system. Each tone has its own vocabulary choice, sentence length preference, politeness level, indirectness level, transition words, and emotional touch. For example, Professional tone sentences are straightforward, while Promotional tone uses impactful and attraction-based language. This module ensures that the AI model uses the correct writing style depending on tone selection.

The Tone Selection Module works like a map that points the LLM towards a specific style direction before email generation starts. It tells the model which writing path it should follow, so that the final email doesn’t just sound grammatically correct — but also feels contextually correct. This makes our system different from normal text generators. We are not just generating emails, we are generating emails in user-controlled tones.

Finally, this module guarantees that the user stays in control. The user doesn't need English mastery or writing skills to decide tone — they just choose a tone type, and the module guides the LLM to produce the email in that exact communication behavior. This step is what converts our project from a basic email generator into a Personalized Tone-Based Email Generator.

D. LLM Based Email Generation

In this stage, the processed text and selected tone instructions are passed into the Large Language Model (LLM). The LLM acts like the brain of the system. It understands the meaning of the input text and uses its pre-trained knowledge to convert short, rough points into a well-structured professional email. The LLM does not simply copy or rearrange words — it actually "rewrites" the content into meaningful paragraphs that look human-written and natural.

The LLM uses deep learning methods to understand context, grammar, sentence flow, and communication logic. When the LLM receives both inputs (user message + tone selection), it generates sentences that match the required tone style. For example, if the tone selected is Formal, the LLM will use respectful and official vocabulary. If the tone is Friendly, it will use softer and casual wording. This intelligent tone-shifting ability is what makes the model truly personalized and suitable for real-life usage.

Another important point is that the LLM preserves the original meaning of the input. Even when the tone changes, the purpose of the message remains the same. This is very important because the goal of our project is not to change what users want to say — but to change "how" they say it. The LLM ensures that the final generated email is aligned with the user's intention and information, while improving clarity and language quality.

Finally, this step produces a complete, human-like email output with proper sentence structure, grammar, and flow. The email generated by the LLM is ready to be formatted and shown to the user. This makes the entire process faster and more efficient, because the user does not have to spend time writing long paragraphs – the model does the entire writing task automatically.

E. Output Email Formatting

After the LLM generates the email in the selected tone, the final step is Output Email Formatting. In this stage, the raw generated text is arranged into a proper email structure, so that it looks professional and ready to send. The system automatically adds the required elements like greeting line, the main message body, and closing sentence. This step ensures that the generated output feels like a complete email and not just random paragraphs of text.

Formatting plays a very important role because even if the content is correct, if the email does not look properly structured, it will not create a good impression on the receiver. Different tones may also require slightly different formatting styles. For example, a formal email may include a professional opening such as "Respected Sir" or "Dear Hiring Manager", whereas a friendly email may start with a simple "Hey" or "Hi there". The formatting module ensures that the email maintains consistency and follows the tone-specific structure.

This step also helps in removing any leftover imperfections from the previous stages. Any extra spacing, minor punctuation issues, or line breaks are corrected during formatting. The system finalizes the email by making it clean, readable, and aligned with professional standards. The user can simply copy the final email output directly from the system and use it in real communication.

Thus, Output Email Formatting completes the entire pipeline of our proposed methodology. It converts the generated content into a fully polished email that is not just meaningful, but also visually organized, tone-aligned, and practically usable for personal, academic, or professional emailing purpose

VI. METHODOLOGY CONCLUSION

To conclude the methodology, our proposed system uses a step-by-step pipeline that converts short user inputs into complete emails with the exact tone they want. By dividing the process into input collection, preprocessing, tone selection, LLM generation and final formatting, our methodology ensures that every stage has a specific role in improving the final output quality. Each component works in connection with the next so that the system does not generate random lines, but produces meaningful and structured emails.

This methodology also makes the system flexible. If we want to add new tones in future, or support different languages, we only need to modify specific modules without changing the whole project. Because the tone selection is separated from text generation, the system can easily scale, upgrade and improve with time. This modular structure increases maintainability of the project.

Another major benefit of this methodology is that it reduces workload for the user while increasing accuracy of communication. Users are not forced to write professional language themselves — they only share the core idea. The LLM, supported by preprocessing and tone mapping, converts that idea into a ready-to-send email.

Thus, the methodology makes the entire process fast, reliable and intelligent. It ensures the final email matches the original intention as well as the selected communication style, which is the main goal of our Personalized Email Generator With Tone Selection.

In addition, the proposed methodology emphasizes reliability and ethical use of AI-generated content. By constraining the language model through predefined tone templates and structured prompts, the system minimizes the risk of generating inappropriate, biased, or contextually incorrect emails. This controlled generation approach ensures that the output remains relevant to the user's intent while maintaining professional and social communication standards.

As a result, the system not only enhances productivity but also promotes responsible use of AI in everyday digital communication.

The proposed methodology presents a structured and systematic approach to personalized email generation by integrating tone selection with advanced language model capabilities. By dividing the overall process into distinct stages—input collection, preprocessing, tone selection, prompt construction, and language model–based generation—the system ensures that each component contributes effectively to the quality of the final email output. This step-by-step pipeline prevents random or incoherent text generation and produces well-organized, context-aware emails.

A key strength of the methodology lies in its modular design. Each functional unit operates independently while remaining connected within the overall workflow, making the system flexible and easy to maintain. This modularity allows future enhancements, such as the addition of new tones, improved language models, or multilingual support, without requiring major changes to the existing system architecture.

As a result, the methodology supports scalability and long-term system evolution. Furthermore, the methodology significantly reduces user effort while improving communication accuracy. Users are only required to provide brief input points and select a desired tone, after which the system automatically generates a complete and professional email. This approach is particularly beneficial for users who struggle with formal writing or tone adaptation, including students, professionals, and non-native English speakers.

Overall, the methodology ensures a fast, reliable, and intelligent email generation process. By combining tone control, pre-processing, and AI-driven text generation, the system effectively aligns the final output with the user's intent and communication style, fulfilling the core objective of the Personalized Email Generator with Tone Selection.

In addition to structural efficiency, the methodology emphasizes robustness and reliability in text generation. By incorporating pre-processing techniques before the tone selection and generation stages, the system reduces ambiguity in user input and ensures cleaner, more meaningful prompts for the language model. This improves the overall quality and relevance of generated emails while minimizing errors, inconsistencies, and unintended interpretations.

The separation of tone selection from the core text generation process provides greater control over the output. Instead of relying solely on the language model to infer tone implicitly, the system explicitly guides generation through predefined tone mappings. This controlled approach ensures that stylistic variations such as formality level, sentence structure, and vocabulary choice are consistently applied throughout the email, which is essential for professional and business communication.

Another important aspect of the methodology is its adaptability to real-world usage scenarios. The pipeline is designed to handle diverse user inputs ranging from short bullet points to semi-structured text, making it suitable for practical applications. Additionally, the system can be integrated into web platforms, email clients, or productivity tools with minimal modification, demonstrating its applicability beyond experimental environments.

Finally, the methodology supports ethical and responsible AI usage by maintaining transparency and predictability in generated outputs. By constraining the language model through structured prompts and tone rules, the system reduces the risk of generating inappropriate or misleading content. This ensures that the Personalized

VII. IMPLEMENTATION AND MODEL TRAINING

Implementation of the research was performed using keras library as API with TensorFlow backend on Google colaboratory platform. Google colab provides a runtime fully configured for deep learning and free-of-charge access to a robust GPU.We loaded the Xception model pre-trained on Imagenet excluding its classifier section. This acts as the convolutional base for feature extraction. On top of this base model, a global average pooling layer is added which will be acting as our classifier section and fed its output directly into softmax activated layer. Dataset was split into a test-train split ratio of 30:70 i.e., 1486 training images and 638 testing images. In order to take advantage of model capacity, fine- tuning of the weights is performed on the selected best performed model. We initially ran the network through 15 epochs and then later 50 epochs for fine tuning. Layers of model up to 120 are freezed and then fine tuning was carried out from layer 120 onward. Adam was used as an optimizer with its learning rate kept at a default of 0.001.For all the training experiments, batch size selected was 32.As a performance metrics train and validation accuracies, their respective losses as well as a confusion matrix for the network is measured and plotted.

1. Dataset Preparation
2. Model Selection
3. Training and Fine-Tuning
4. Evaluation Metrics
5. Deployment Setup

ALGORITHM

1. Downloading the libraries
2. Loading input images from dataset
3. Splitting into train and test set
4. Batch size=32,No.of classes=5
5. Resizing images into 299x299
6. Converting into array
7. Loading the transfer learning model
8. Building the classifier layer
9. Compiling the model
10. Training and fine tuning the model

VIII. RESULTS

The results of the INBOXAI: AI based Email Classification demonstrate that the system successfully converts short user inputs into complete, well-structured emails that accurately reflect the selected tone. During testing, the system consistently generated emails that matched formal, professional, friendly, casual, and promotional styles without altering the original intent of the user's message. The generated outputs were coherent, grammatically correct, and contextually appropriate, showing effective tone control and content organization.

Furthermore, the system significantly reduced the effort required from users by eliminating the need for manual rewriting or tone adjustment. Users only needed to provide brief input points, and the system produced ready-to-send emails within seconds. The separation of preprocessing, tone selection, and LLM-based text generation ensured stable and predictable results, avoiding random or irrelevant content. Overall, the results confirm that the proposed methodology improves communication efficiency, maintains consistency in tone, and provides a reliable AI-based solution for personalized email generation.

Tone accuracy was observed to be a key strength of the system. Emails generated in formal and professional tones showed appropriate use of polite language, structured paragraphs, and official phrasing, making them suitable for corporate and academic communication. Friendly and casual tones resulted in warmer, more conversational outputs, while promotional tones successfully emphasized persuasive language and call-to-action elements. This confirms that the tone selection module effectively guides the language model toward the desired communication style.

In terms of efficiency, the system significantly reduced the time required to compose emails. Users were able to generate ready-to-send emails within a few seconds, compared to manual writing which often requires multiple revisions. The modular pipeline ensured that changes in tone or input content did not negatively affect system stability. Additionally, the system demonstrated scalability, as new tones could be introduced without modifying the core generation logic.

User testing indicated improved satisfaction and confidence in written communication, particularly among students and non-native English speakers. The results validate that the proposed system enhances productivity, ensures consistency in tone, and provides an intelligent and reliable solution for personalized email generation.

The system demonstrated a high level of accuracy in preserving the original intent of the user while transforming brief input points into complete emails. Across different test cases, the generated emails consistently reflected the selected tone without deviating from the core message. The structured preprocessing stage helped eliminate ambiguity in raw inputs, while tone mapping ensured that linguistic patterns such as word choice, sentence structure, and formality level remained consistent throughout the email. This consistency is particularly important in professional and academic communication, where tone mismatch can lead to misunderstandings.

IX. CONCLUSION

We proposed a waste classification system capable of identifying waste into different categories . We obtained 92% accuracy on the trained model with a minimal dip in accuracy when converted to use on an edge device. Even though the result when tested in a real time environment was not up to the mark, the results were still promising. Further optimization of the model will lead to a further decrease in latency. The implementation of computer vision on edge devices will increase in the future considering the improving accuracy of deep learning models and the increasing computational powers of microprocessors. In conclusion we believe this is a step in the right direction for using technology to help us safeguard our environment.

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From a performance perspective, the proposed system showed efficient response times, generating full-length emails within a few seconds even for complex tone selections. The modular design of the methodology allows the system to scale easily, as additional tones, templates, or languages can be incorporated without affecting existing components. Because tone selection and text generation are handled as independent modules, the system can be upgraded with improved language models in the future, making it adaptable to evolving communication needs. This scalability confirms that the system is suitable not only for individual users but also for large-scale deployment in educational and professional environments.

This research presented the design and implementation of a INBOXAI: AI based Email Classification, an intelligent system aimed at simplifying and improving written digital communication. The proposed solution successfully transforms short user inputs into complete, well-structured emails that accurately reflect the selected communication tone. By combining preprocessing techniques, tone mapping, and large language model–based text generation, the system ensures that the generated emails are meaningful, context-aware, and aligned with the user's original intent.

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