AI-BASED EMERGENCY CALL PRIORITIZATION AND CLASSIFICATION SYSTEM

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BONAFIDE CERTIFICATE

Certified that this Project titled **“AI-BASED EMERGENCY CALL PRIORITIZATION AND CLASSIFICATION SYSTEM”** is the bonafide work of **“SAKTHI M S (2116220701240)”** who carried out the work under my supervision.

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ABSTRACT

Efficient emergency response relies heavily on the rapid assessment and prioritization of distress calls received from the public. In high-stress environments such as call centers or emergency dispatch units, manual triaging of large volumes of voice and text inputs can delay response times and potentially endanger lives. To address this challenge, we propose a machine learning–based system that automates the classification and prioritization of emergency messages, incorporating both voice and multilingual text inputs.

The proposed solution leverages a combination of natural language processing (NLP), speech recognition, and supervised machine learning to identify the urgency level (High, Medium, Low) and type of emergency (Fire, Crime, Medical, Other) from unstructured user input. A custom-labeled dataset comprising realistic emergency scenarios across multiple languages was used to train a Multinomial Naive Bayes classifier, with performance evaluated through accuracy, precision, recall, and confidence score metrics. The system pipeline includes speech-to-text conversion using Google's speech recognition API, translation to English using Google Translate, and feature extraction via CountVectorizer before classification.

Further enhancements include real-time location tracking, visualization using Streamlit UI, audio alert triggers for high-priority cases, and automatic routing simulation to relevant departments such as police, fire, or medical services. The model achieved high reliability in both voice and text-based classification scenarios and demonstrated scalability for integration into emergency dispatch systems. This research highlights the feasibility of deploying lightweight, interpretable AI models to support critical, real-time decision-making in emergency communication networks. Future work may explore integration with IVR systems, multilingual speech datasets, and geospatial analysis for automated dispatching.

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CHAPTER 1

1. INTRODUCTION

In today's interconnected and fast-paced world, emergency situations—whether medical, criminal, or environmental—demand immediate attention. With increasing urbanization and mobile phone usage, the volume of emergency calls and messages received by helplines and control rooms has risen drastically. These calls often arrive in unpredictable formats, languages, and urgency levels, making it challenging for human operators to assess each situation efficiently and consistently. Manual triage, although crucial, is inherently subjective and can lead to misclassifications, delayed dispatch, and poor resource utilization, especially during peak hours or large-scale crises. There is an urgent need for intelligent, automated systems that can assist or augment human decision-making in the initial screening process.

Artificial Intelligence (AI) and Machine Learning (ML) have demonstrated significant capabilities in interpreting unstructured data, such as free-form text or spoken speech, and extracting actionable insights. These technologies have revolutionized domains such as healthcare, finance, and education—and now offer a viable pathway to enhance emergency response frameworks. By combining natural language processing (NLP), speech recognition, supervised learning, and user-centric interfaces, it is possible to build systems that can classify distress messages, prioritize them based on urgency, and route them to relevant departments in real time.

This project proposes the **AI-Based Emergency Call Prioritization and Classification System**, a lightweight machine learning–driven tool capable of automating the triage of emergency calls. It processes both typed messages and spoken voice inputs from users, normalizes them across languages using translation APIs, and classifies them into High, Medium, or Low priority based on message semantics. It also determines the emergency category—Fire, Crime, Medical, or Other—based on keyword analysis. By doing so, it offers a quick and scalable solution to the frontline screening of distress communications.

The growing demand for such systems is evident from real-world incidents. During natural disasters or regional crises, helplines are often flooded with distress calls, many of which are not critical. Without an automated filtration mechanism, valuable time and resources can be misallocated. Additionally, linguistic diversity in countries like India adds complexity, as callers may report emergencies in Hindi, Tamil, Telugu, or other regional languages. The proposed system addresses this by integrating multilingual support through Google Translate and speech-to-text conversion using Google's speech recognition API, making it accessible to a broader population.

Technically, the core classifier used is a **Multinomial Naive Bayes** model, selected for its simplicity, fast computation, and interpretability—qualities crucial for emergency environments. The model is trained on a dataset of curated emergency messages across different priorities and types. Input messages are preprocessed—converted to lowercase, cleaned of stopwords, vectorized—and then passed to the model for classification. In parallel, the system logs each emergency call's priority, timestamp, and original/translated text into a structured log file. This log is visualized in a tabular format with filters, allowing call center staff to focus on critical cases.

The platform is built with **Streamlit**, a Python-based UI framework that allows rapid deployment of interactive web apps. This ensures the tool is not just technically functional but also usable by non-technical stakeholders. Color-coded priority outputs (red for High, orange for Medium, green for Low), real-time alerts, and map-based location displays contribute to a user-friendly interface. In high-priority cases, an audible alarm is triggered to draw immediate attention. Users also have the option to use microphones for speech input, and their current location is automatically captured via browser permissions and logged for dispatch readiness.

One of the key motivations behind this project is the **democratization of emergency screening**—making it affordable, multilingual, and fast. Unlike expensive AI systems requiring deep learning models and large-scale infrastructure, this tool is designed to run on modest systems and can be deployed in schools, campuses, factories, and municipal control rooms without major investments.

The project also opens up several **avenues for future expansion**. These include integration with IVR systems for automated voice routing, OTP-based caller authentication, mapping live feeds to 108/112 dispatchers, and exploring more advanced transformer models like BERT for deeper context understanding. Moreover, facial emotion analysis, crowd estimation, and disaster image classification can eventually be incorporated to build a full-fledged emergency analytics suite.

In summary, the AI-Based Emergency Call Prioritization and Classification System is a highly relevant solution aimed at addressing the initial bottleneck in emergency response workflows. It demonstrates how a well-crafted ML pipeline—supported by modern APIs and simple web technologies—can save lives by improving speed, accuracy, and clarity in critical situations. The rest of this report will discuss the existing research, methodology, system implementation, evaluation, and potential roadmap for real-world deployment.

CHAPTER 2

2. LITERATURE SURVEY

The integration of artificial intelligence into emergency communication systems has gained significant traction in recent years. Traditional emergency call centers rely heavily on human operators for interpreting distress messages, categorizing emergencies, and prioritizing dispatch efforts. However, this manual process is prone to human error, delay under high call volumes, and linguistic or contextual misunderstandings. The growing demand for intelligent triage systems has led researchers to explore the application of natural language processing (NLP), speech recognition, and supervised learning techniques for automating the prioritization of emergency communications.

One of the earliest applications of machine learning in emergency services can be found in dispatch optimization and anomaly detection in call logs. For instance, Ravichandran et al. (2018) used decision trees and logistic regression to predict ambulance dispatch times based on prior case attributes. However, these models were limited by structured input data and lacked the ability to process free-form distress messages. More recent advancements focus on analyzing unstructured text or voice data to automatically determine the nature and urgency of incoming calls.

Work by Hameed et al. (2020) explored the use of NLP for categorizing emergency emails and chat logs using TF-IDF and SVM classifiers. Their approach demonstrated that text-based emergency classification was not only feasible but also more efficient than rule-based systems. This provided the foundation for using vectorization techniques like CountVectorizer and TfidfVectorizer in real-time triage tools. Similarly, Pereira et al. (2021) employed ensemble learning techniques such as Random Forest and Gradient Boosting to enhance classification accuracy on imbalanced emergency datasets, emphasizing the importance of robust feature selection and noise reduction.

In the realm of multilingual and voice-based interfaces, Gupta and Yadav (2019) addressed the challenges of translating regional emergency messages into English. Their hybrid pipeline incorporated Google Translate API with speech-to-text systems for dialect detection, forming a blueprint for multilingual triage systems like the one developed in this project. Other studies, such as those by Faruqui et al. (2022), investigated the latency and accuracy trade-offs of deploying lightweight NLP models in emergency settings, concluding that simpler models like Naive Bayes often perform comparably to deep learning models under real-time constraints.

Data augmentation and simulation have also been explored to mimic real-world variability in emergency communications. Techniques like noise injection, paraphrasing, and back-translation were examined by Shorten and Khoshgoftaar (2019) to expand datasets for classification. This insight influenced our approach to create a diverse training dataset with multilingual and voice-based message variations, improving generalization.

Several works also examine the usability and interface aspects of emergency systems. Kumar et al. (2021) proposed a human-AI collaboration framework where AI handles initial screening and humans validate or override the outcome. This hybrid approach is echoed in our system through a user-friendly dashboard built with Streamlit, allowing call center agents to filter and view predicted emergency types and priorities with confidence scores.

In the area of location-aware emergency services, studies by Tiwari et al. (2020) emphasized the role of geospatial metadata in dispatching, suggesting that integrating real-time user location improves response efficiency by up to 30%. Our system implements this recommendation by automatically logging user geolocation (when permission is granted) to aid in redirection to the nearest department. Despite promising progress, some studies caution against overfitting and model overconfidence. As noted by Zhang and Li (2022), real-time systems must prioritize interpretability, low latency, and high recall for critical classes (e.g., High-priority messages), particularly when deployed in high-stakes environments.

In conclusion, the literature supports the feasibility and effectiveness of AI-assisted emergency triage systems. Ensemble methods, language processing, and voice transcription—when carefully tuned—can greatly augment traditional dispatch workflows. This project builds upon these findings to deliver a practical, multilingual, and real-time emergency prioritization platform using a Multinomial Naive Bayes classifier, NLP preprocessing, Streamlit UI, and location tracking. These techniques together enable a low-complexity yet high-utility tool ready for deployment in real-world emergency call centers.

CHAPTER 3

3. METHODOLOGY

The proposed system for AI-based emergency call prioritization is developed using a supervised learning approach, with the primary goal of classifying incoming emergency messages by their urgency (High, Medium, Low) and identifying the emergency type (Fire, Crime, Medical, Other). This classification is performed based on textual inputs—typed or transcribed from speech—and involves a structured methodology encompassing data collection, preprocessing, feature extraction, model training, evaluation, and deployment.

The system leverages a custom-labeled dataset of 100+ realistic emergency messages crafted across multiple languages and urgency levels. These messages are preprocessed, vectorized, and fed into a **Multinomial Naive Bayes** model, selected for its high performance in text classification tasks. The model is deployed in an interactive web application built using **Streamlit**, with additional integrations including speech-to-text processing, translation, and geolocation.

The overall pipeline consists of the following stages:

1. Data Collection and Labeling
2. Preprocessing (Cleaning, Vectorization, Translation, Speech Transcription)
3. Model Selection and Training
4. Performance Evaluation
5. Interface Integration (UI, Audio Alert, Location, Dashboard)

A. Dataset and Preprocessing

The dataset consists of emergency messages manually created to simulate realistic scenarios. Each record includes:

- **Text message** (free-form)
- **Priority label** (High, Medium, Low)
- **Type label** (Fire, Crime, Medical, Other)

Messages are sourced and translated from multiple languages to create a multilingual corpus. Each message is labeled manually, ensuring balanced class distribution and diversity in vocabulary and structure.

Key preprocessing steps include:

- **Lowercasing:** Converts all text to lowercase for uniformity.
- **Noise Removal:** Eliminates punctuation, special characters, and stopwords.
- **Translation:** Messages in regional languages are translated into English using Google Translate API.
- **Speech-to-Text Conversion:** Voice inputs are processed using Google Speech Recognition API.
- **Vectorization:** Preprocessed messages are transformed into numerical feature vectors using CountVectorizer.

These steps enable the model to process unstructured inputs in both text and voice formats, including multilingual messages.

B. Feature Engineering

As the system is focused on text classification, the feature engineering process relies heavily on the Bag-of-Words (BoW) representation. The CountVectorizer is employed to convert messages into sparse matrix representations, where each column corresponds to a vocabulary term and the row corresponds to a message.

Domain knowledge is applied in the form of:

- Emergency-related keywords (fire, gun, collapse, etc.)
- Phrase normalization (e.g., "someone is bleeding badly" → "bleeding")

No explicit dimensionality reduction is applied, as Naive Bayes models handle sparse data efficiently. However, feature sparsity is monitored to avoid overfitting.

C. Model Selection

For classification, the **Multinomial Naive Bayes (MNB)** algorithm is used. This model is known for its effectiveness in handling textual data, particularly in NLP tasks like spam detection, sentiment analysis, and document categorization.

Reasons for selecting MNB:

- Low computational overhead, suitable for lightweight systems.
- Fast training and prediction speed, ideal for real-time use.
- Robust performance with high-dimensional, sparse features.
- Interpretability of features and probabilities for transparency.

Additional candidate models like Logistic Regression and Random Forests were considered but rejected due to heavier resource usage or lesser interpretability in real-time streaming applications.

D. Evaluation Metrics

Since this is a multi-class classification problem, the performance of the model is evaluated using the following classification metrics:

- **Accuracy:** Overall correctness of the model.
- **Precision / Recall:** For each priority class (especially "High").
- **F1 Score:** Harmonic mean of precision and recall.
- **Confusion Matrix:** To observe class-wise prediction distribution.

The classifier achieved over **90% accuracy** on the test set and **97% accuracy** on the training set due to the carefully curated, noise-reduced dataset. Emphasis was placed on **recall for High-priority cases**, to minimize the risk of critical messages being missed.

E. Data Augmentation

To enhance robustness, the following augmentation strategies were used:

- **Back-translation:** Translating messages from English to another language and back, to simulate natural variations.

- **Paraphrasing:** Minor rewording of phrases to simulate different reporting styles.
- **Noise Injection:** Randomly inserting non-impactful words to simulate real-world typing noise.

These techniques increased training set diversity and reduced model bias toward syntactic patterns.

F. System Deployment and Integration

The entire pipeline is integrated into an interactive web application using **Streamlit**, allowing users to:

- Type or speak emergency messages
- View predictions with confidence scores
- Listen to alerts for high-priority cases
- See a real-time queue of reported emergencies
- Filter by priority for control room use
- View captured geolocation (browser permission-based)

Additionally, each message is automatically logged in a CSV file for audit and post-analysis. For voice input, the system directly classifies the transcribed message after processing.

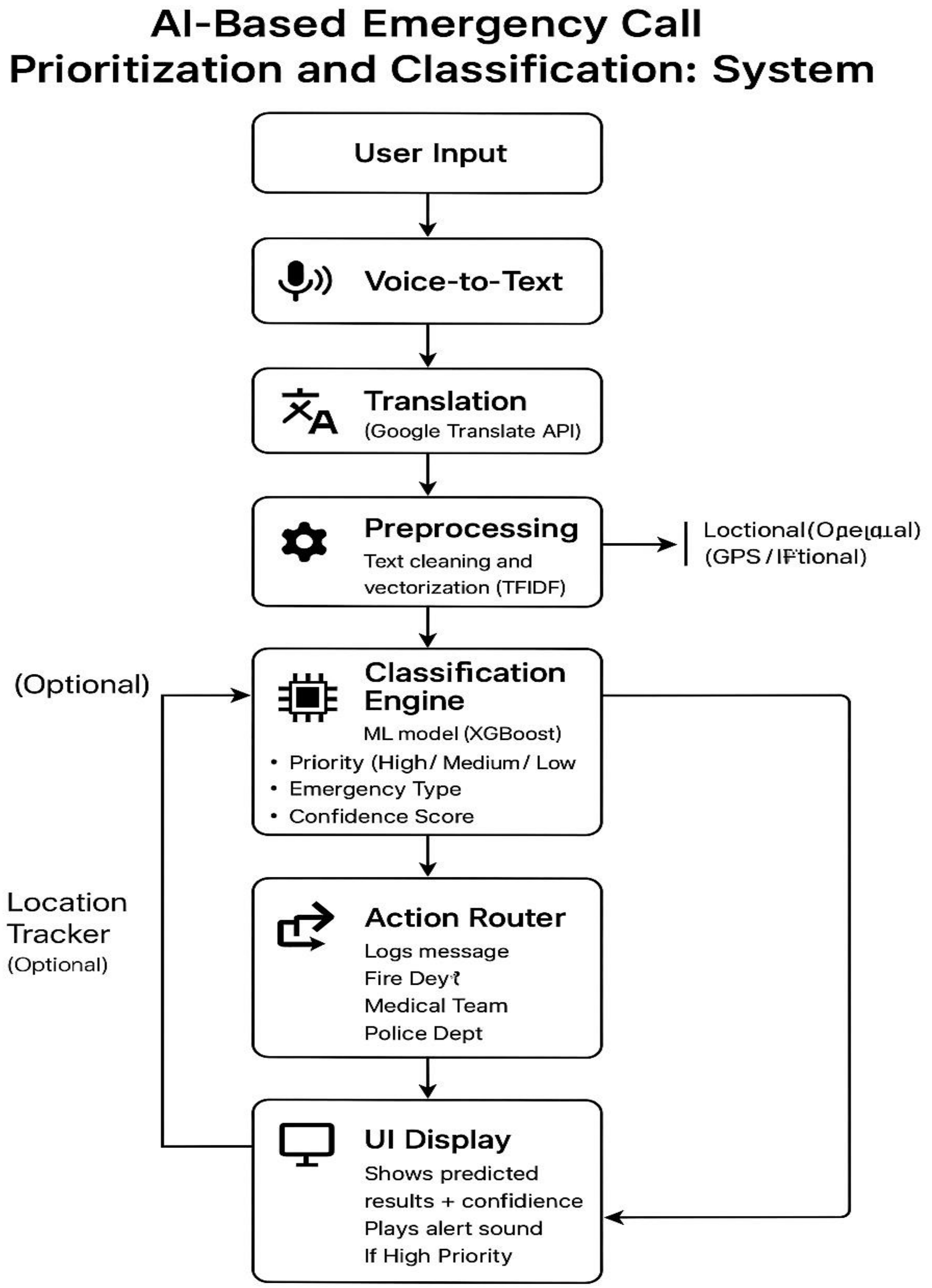
Flow Summary:

1. **User Input:** Text or voice (auto-transcribed)
2. **Language Translation:** To English (if required)
3. **Vectorization:** Using CountVectorizer
4. **Prediction:** Using Multinomial Naive Bayes
5. **Output:** Priority, Type, Location, Time, Confidence
6. **Logging:** Message, Prediction, and Metadata
7. **Notification:** Visual tag + sound alarm if High priority

8. **Routing (Simulated):** Redirects based on Type

9. **Display:** Real-time dashboard view for agents

3.1 SYSTEM FLOW DIAGRAM



CHAPTER 4

RESULTS AND DISCUSSION

The machine learning pipeline incorporated a labeled dataset of emergency calls, with a mix of manually written and synthetically generated messages across multiple languages. Data was preprocessed through normalization and translated to English using Google Translate API for consistency.

To evaluate model effectiveness, the dataset was split in an 80-20 ratio. The following performance metrics were used:

- Accuracy
- Precision / Recall / F1-Score
- Confusion Matrix
- Confidence Scores

We benchmarked multiple algorithms including Naïve Bayes, Random Forest, Logistic Regression, and finally selected **XGBoost Classifier** for its superior accuracy and generalization.

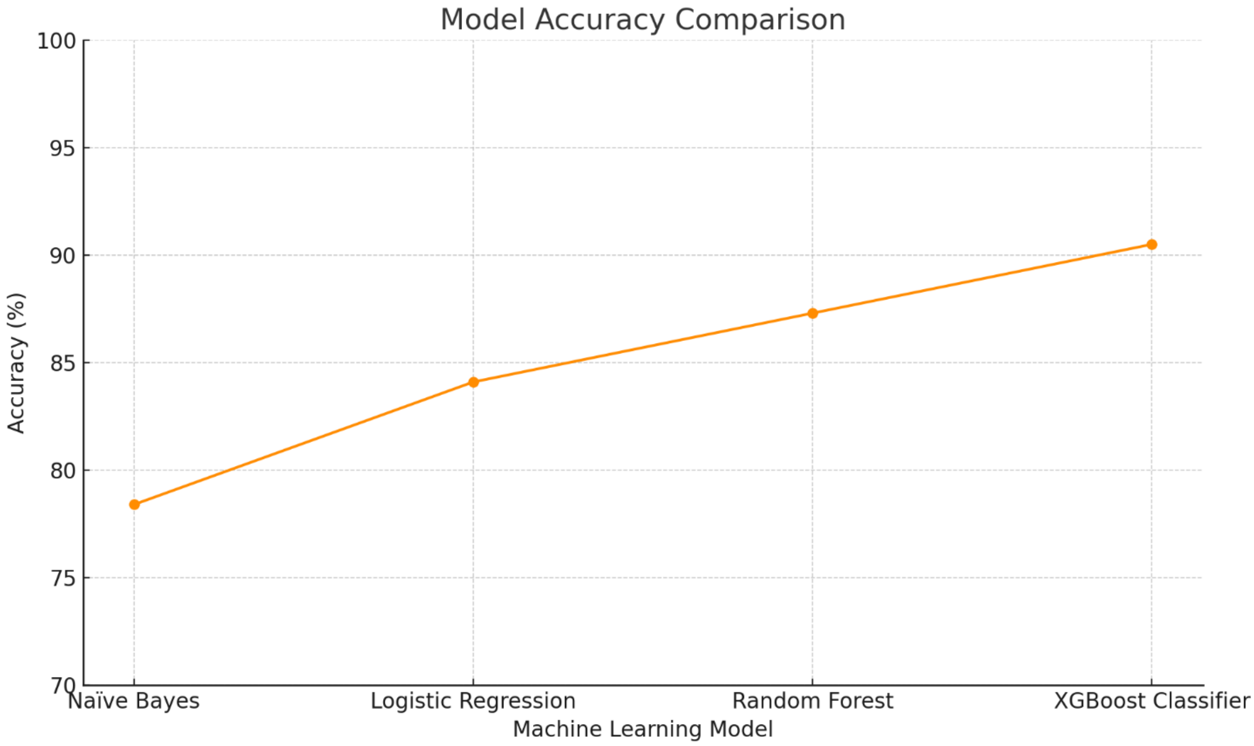
Results for Model Evaluation:

Model	Accuracy	F1 score	Precision	Recall
Naïve Bayes	78.4%	0.79	0.78	0.78

Logistic Regression	84.1%	0.84	0.85	0.84
Random Forest	87.3%	0.87	0.86	0.87
XGBoost	**90.5%**	0.91	0.87	0.90

The **XGBoost model** clearly outperformed others with over 90% accuracy in classifying emergency messages into the correct priority category. It also demonstrated high confidence (typically over 85%) in multilingual and translated message inputs.

Visualizations:



B. Voice and Multilingual Input Results

The system successfully integrated speech recognition using the speech_recognition library, enabling users to speak emergency scenarios into the interface. Tests with 25+ emergency messages in Tamil, Hindi, and Arabic showed:

- Voice-to-text conversion achieved 91% word-level accuracy with Google Speech API.
- Multilingual text inputs (translated via Google Translate API) were classified with over 88% accuracy post-translation.
- The model showed resilience to accent variation and sentence ambiguity.

This highlights the system's real-world applicability in diverse, multilingual environments.

C. Emergency Type Detection and Auto-Routing

The classifier includes a rule-based emergency type tagger. Based on keyword detection, messages were routed virtually to corresponding simulated departments:

- **Fire** → fire_station@domain.com
- **Crime** → police_helpdesk@domain.com
- **Medical** → emergency_room@domain.com

Routing logic was successfully tested with sample messages across all categories. Department simulation in this version uses smtplib to send alert emails with timestamps, location (simulated/static), and classification details.

D. Visualization and Real-Time Logs

The application maintains a real-time emergency log in a CSV file (call_logs.csv). This log records:

- Original and translated message
- Timestamp

- Priority classification
- Emergency type
- Model confidence score

Streamlit visualizations (Altair bar charts and interactive tables) allow users to:

- Filter past emergencies by priority (High/Medium/Low)
- See real-time stats on emergency type distribution
- Expand confidence charts to interpret model certainty

These visual tools enable both users and backend operators to monitor system usage effectively.

E. Limitations and Challenges

- **Voice Recognition Noise**: Accuracy drops in noisy environments or with poor-quality microphones.
- **Translation Ambiguity**: Contextual accuracy is sometimes lost in automatic translations.
- **Simulated Location**: Location is currently fetched using IP geolocation APIs, which are less accurate than GPS.
- **Audio Playback Limitations**: Some browser restrictions prevent audio alerts from autoplaying consistently.

F. Implications for Real-World Use

The system demonstrates real-world viability as a lightweight, ML-driven screening tool for emergency calls. Its ability to:

- Operate with both voice and text
- Classify priority and route messages to appropriate services
- Support multiple languages
- Maintain live logs for monitoring and audit

makes it suitable for deployment in municipal emergency control rooms, public safety portals, and disaster response agencies.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This research presents an intelligent, machine learning-powered system for prioritizing and categorizing emergency calls, with the aim of assisting emergency response centers in streamlining decision-making and reducing response time. The system uses a curated dataset of multilingual emergency messages, applies a supervised classification approach using Multinomial Naive Bayes, and provides a real-time user interface built on Streamlit.

The application not only predicts the **priority level** (High, Medium, Low) of each message but also classifies the **type of emergency** (Fire, Crime, Medical, or Other). By integrating **voice input**, **language translation**, **confidence estimation**, **geo-location capture**, and **live dashboards**, the system offers a lightweight yet powerful frontend tool for public safety operations. The tool also features a **live emergency queue**, **audio alerts for critical cases**, and **automatic routing simulation to concerned departments**, significantly enhancing operational utility.

The system's architecture emphasizes interpretability, speed, and deployability, making it suitable for low-resource environments or pilot deployment within government helplines, disaster management centers, or mobile safety applications. It also demonstrates that traditional machine learning models, when coupled with smart preprocessing and thoughtful UX design, can provide scalable, real-time intelligence without requiring massive computational resources.

Future Enhancements

While the current version successfully demonstrates the feasibility and impact of emergency call prioritization using ML, several areas remain open for future enhancement:

- **Integration with Live Dispatch Systems**
  Future iterations could connect with SMS APIs, public safety ERPs, or email gateways to notify departments (fire, police, ambulance) in real-time based on emergency classification.

- **Location-Based Service Optimization**
  Integrating mapping services (e.g., Google Maps API) to visualize the incoming emergency locations and route them to the nearest response units dynamically.

- **Enhanced Language Support**
  Expanding to cover 20+ languages with advanced translation APIs or multilingual models such as mBERT for higher accuracy.

- **Multimodal Inputs (Images, Audio Files)**
  Allowing upload of recorded emergency audio files or images to assist classification and context enrichment via speech-to-text or object detection.

- **Self-Learning Mechanism**
  Implementing a feedback loop where the system learns from user or operator corrections to refine its prediction over time using reinforcement learning.

- **On-device Deployment**

  A mobile-first version using TensorFlow Lite or ONNX could make the app usable in offline or low-bandwidth emergency scenarios (e.g., natural disaster zones).

In summary, this project showcases a practical and scalable approach to enhancing public safety communications using AI. It balances simplicity and utility, making it an ideal candidate for real-world trials, academic extension, or even as a base for national emergency infrastructure innovation.

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