Leveraging NLP and ML to Accelerate Lifesaving 911 Care for Cardiac Arrest, Myocardial Infarction, Infectious Emergencies, and Stroke.

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Contacting 911 is the first step followed by every person whenever there is an emergency. The right course of action taken by the 911 system can save the lives of many. Nevertheless, it takes a lot of work for a dispatcher to act carefully on the next step after receiving a 911 call. Understaffing has become one of the most severe problems faced by dispatch centers. It is not an easy job for a single person to listen carefully to every call without missing minute details, requesting suitable queries, and taking the most reasonable step after the call ends. With this project, we aim to prevent mishaps caused by miscalculations of the situation by developing a machine learning model based on supervised learning that analyzes 911 calls in real-time and assists dispatchers in determining whether patients are suffering from a heart attack, stroke, cardiac arrest, or trauma so that the appropriate service can be dispatched. We also aim to create a scoring system for the dispatcher for quality improvement of the approach.

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1 KEYWORDS

Audio calls, Dataset Linking, 911 care, NLP, Machine Learning

2 INTRODUCTION

Emergency dispatch centers, or 911 centers, are locations where qualified personnel receive and handle emergency calls. The 911 operator will inquire about the area and type of emergency when someone dials 911. The relevant emergency services, such as police, fire, or medical professionals, are sent to the caller's location once the information is input into a computer system. While the emergency responders are enroute, dispatchers may give first aid instructions or other assistance to the caller while they remain on the line with them until aid arrives. Every day, the 911 center acts as a vital conduit between the general public and emergency services, saving many lives.

For today's 911 centers, understaffing and less skilled personnel can present serious difficulties. Callers may have to wait longer, and emergency response times may be delayed when a center is understaffed because dispatchers may get overwhelmed by the number of incoming calls. Less experienced staff may also have different training or expertise than a dispatcher with more experience, which increases the possibility of errors and mishaps.

Listening carefully to emergency calls and accurately analyzing the situation can be challenging for 911 operators. The calls they receive can be emotionally charged and chaotic, making it challenging to extract critical information quickly and make the right decisions. Moreover, operators must adhere to strict protocols and procedures while handling emergency calls to ensure the appropriate response is promptly dispatched. This can be incredibly challenging during high-pressure situations when every second counts. Fatigue, stress, and distractions can all increase the likelihood of mistakes. Even the most skilled and knowledgeable operators might err in such circumstances, emphasizing the necessity for continual instruction and assistance.

There is always potential for improvement, even if existing dispatch systems have unquestionably increased the efficiency and accuracy of emergency response. The overwhelming number of calls and data that operators must manage in today's dispatch systems is a typical issue, making it challenging to select and dispatch the appropriate vehicle for each emergency rapidly.

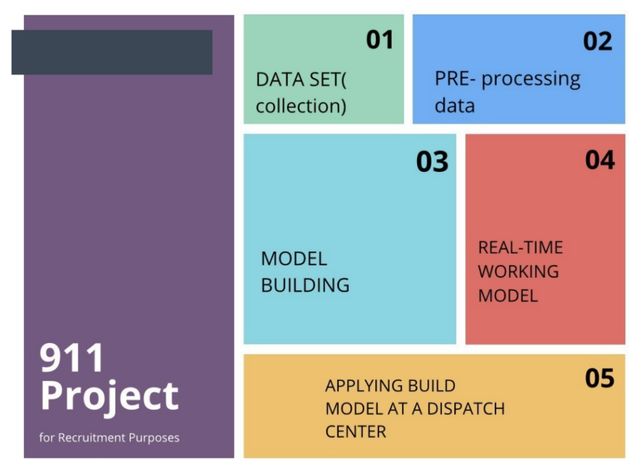

Fig. 1. Methodology

Modern dispatch systems are utilizing machine learning (ML) and artificial intelligence (AI) technology to evaluate data and improve dispatch decisions in order to solve this problem. For example, for each emergency, the optimum vehicle and route may be determined

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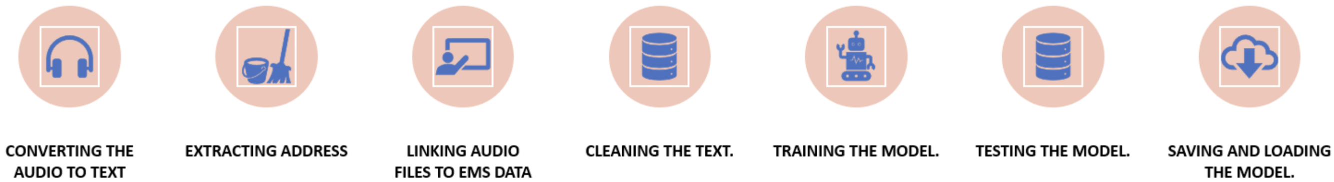

Fig. 2. Basic Model

by automatically analyzing real-time data from many sources, such as GPS monitoring, traffic patterns, and weather conditions. This can speed up reaction times and lower the chance of human decision-making mistakes.

In order to get the best idea about the working of dispatch centers, the team visited dispatch centers and understood the working of every step. This helped us understand the problem dispatch centers are facing and what we can create with the help of technology that will help us ease the work of the 911 dispatchers. After quality meetings and discussions, we created the idea of a supervised machine learning model that used natural language processing to accelerate the 911 care process. Our model analyzes 911 calls in real time and assists dispatchers in determining whether patients are suffering from a heart attack, stroke, cardiac arrest, or trauma so that the appropriate service can be dispatched.

3 RESEARCH HYPOTHESES AND GOALS

3.1 Hypotheses:

“This study hypothesizes that implementation of natural language processing techniques in the analysis of 9-1-1 calls will enable the development of a machine learning model that can improve the efficiency of 9-1-1 care centers, leading to the dispatch of accurate resources and real-time decision-making support for dispatchers.”

3.2 Hypotheses Definition:

According to the research hypothesis proposed in this study, it is conceivable to create a machine learning model that can considerably increase the effectiveness of 9-1-1 care centers by using natural language processing techniques to the analysis of 9-1-1 calls. It is anticipated that the application of such a model will result in the dispatch of precise resources and real-time decision-making support for dispatchers.

The hypothesis effectively states that it is possible to increase the precision and responsiveness of emergency response services by utilizing natural language processing techniques. The well-being of individuals who require immediate medical attention or other emergency services as well as public safety may be significantly impacted by this. The use of natural language processing techniques does truly increase the effectiveness of 9-1-1 care centers will be proven or disproven through empirical study and data analysis.

3.3 Goals:

- To develop a real-time machine learning model to assist dispatchers in determining the emergency services needed for heart-attacks, strokes, cardiac arrest, and trauma.
- To create a scoring system to measure the quality of the dispatcher’s decision-making process, with the aim of improving emergency response outcomes.

4 LITERATURE REVIEW

The 911 service is critical in our country’s emergency response and disaster readiness system. Traditional 911 care concerns dispatching emergency responders, such as police officers, firefighters, or paramedics, to the location of an emergency. When someone dials 911, a qualified operator evaluates the circumstances and dispatches the appropriate responders. Traditional dispatch systems have a proven record of accomplishment of working well in emergencies [1]. These systems have been refined over decades to be as effective and efficient as possible. Many new algorithms are being devised to improve the performance of dispatch systems. Techniques like merging two dispatch systems were tried, and it is observed that it can lead to improved efficiency and expense savings [2]. New algorithms like the "Ambulance telephone triage using ’NHS Pathways’[3] to identify adult cardiac arrest " and "Implementing the ALERT algorithm, a new dispatcher-assisted telephone cardiopulmonary resuscitation protocol"[4] are developed to improve the implementation of 911 care in specific situations of cardiac arrest, stroke, Etc. Despite several improvements, traditional 911 care had drawbacks like long response time, wrong situation analysis, lousy communication, lengthy questionnaire, etc.

CADs were introduced in the early 1970s. Computer-Aided Dispatch (CAD) systems have become critical to modern emergency response infrastructure [5]. CAD systems allow for real-time management and tracking of emergency incidents, including the dispatch of emergency responders, and monitoring their progress [6]. Although the CADs were initially seen as massive systems that were not cost-friendly, they became an interoperable, nimble platform that works to simplify communication between 911 and first responders [7]. In addition, these systems provide dispatchers with an integrated platform for handling emergency calls, assigning resources, and communicating with responders in the field.

The 911 CAD systems provide distinctive features like Offsite data backup, Disaster recovery, Connection to multiple internal

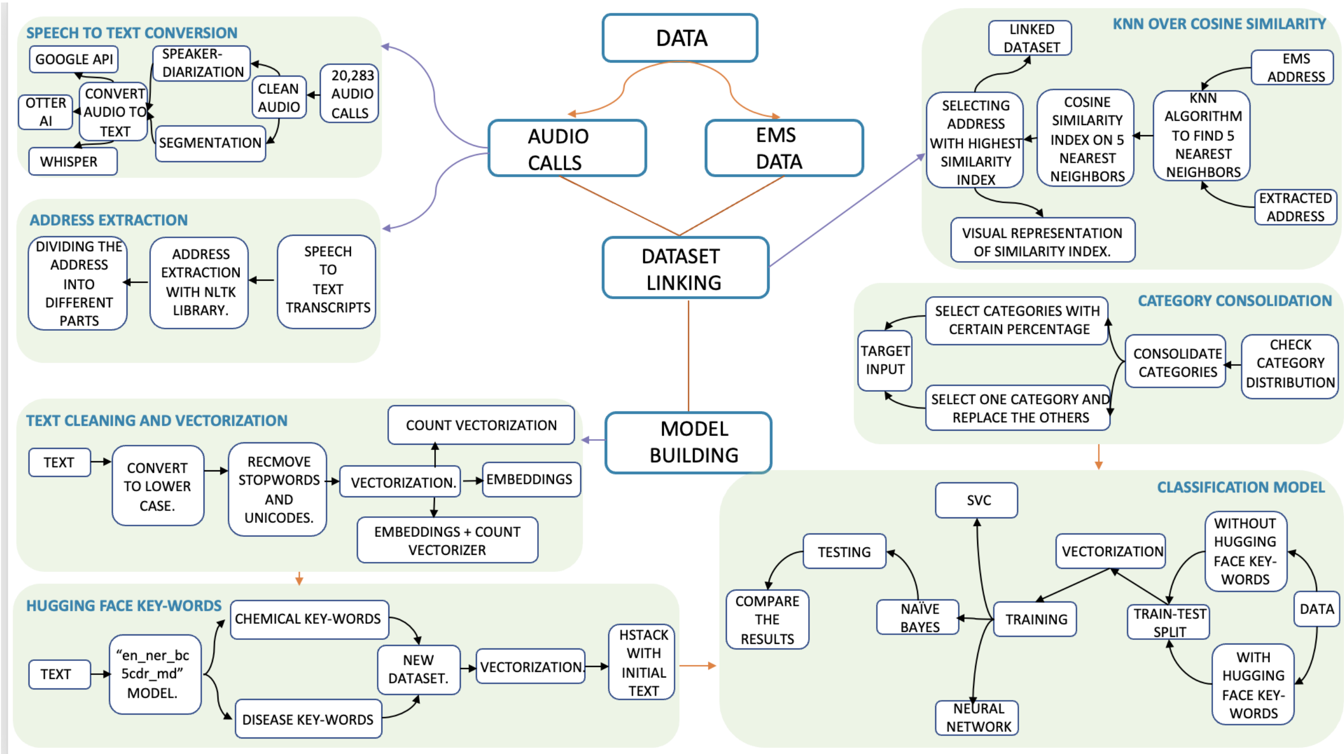

Fig. 3. Improved Model

and external databases, integrated automatic vehicle location, Text-integrated CAD, etc. [8]. In addition, CAD systems can be integrated with various existing solutions in an agency, such as emergency dispatch software, mobile data applications, and location verification software. There have been several recent developments in 911 CAD systems that are changing the way emergency response services operate [9].

Some of the recent developments in CAD include conveying data such as pictures and videos to the first responders on their way to the incident to improve awareness of the situation and obtain more information about an individual during an emergency, connecting with wearable technology used by consumers. All these developments have enabled 911 care to accelerate its dispatching of vehicles faster than usual.

All the above CAD systems have excellent communication techniques, transportation, tracking, mapping, and many more excellent features to help dispatch a vehicle as fast as possible. Nevertheless, from all the research, we observed that most of the dispatch systems, including the CAD systems currently available, require much human involvement, leaving room for human error. The main job of talking to the caller, filling in the details, asking the right questions pertaining to the situation, analyzing the cause, informing the first responder, and dispatching the right vehicle lies in the hand of the 911 operator. The most severe problem today's 911 centers face is understaffing and a less experienced workforce. It is also very tedious for the operator to listen carefully to all the calls and

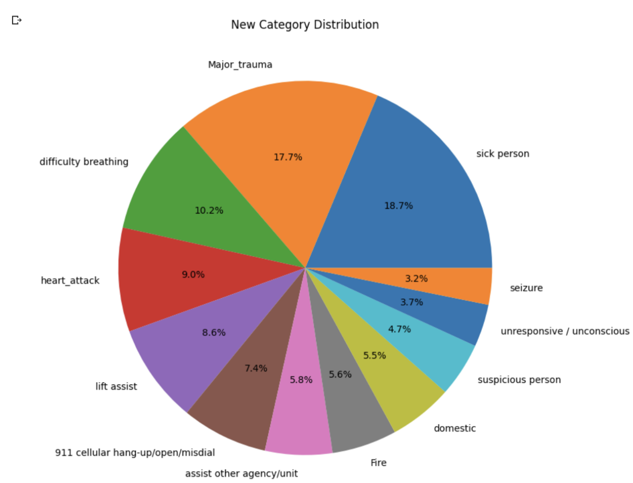

Fig. 4. Category Consolidation

analyze the situation precisely. This increases the scope for error. None of the dispatch systems presently in use ease the work of the operators and improve the efficiency of dispatching the right vehicle. But our model analyzes 911 calls in real-time and assists dispatchers in determining whether patients are suffering from a heart attack, stroke, cardiac arrest, or trauma so that the appropriate service can be dispatched.

5 BACKGROUND RESEARCH AND WORK POSITIONED AGAINST THAT RESEARCH

We examined several pre-existing research papers and internet sources as part of our background investigation to gain the most comprehensive grasp of the 911 dispatch situation. Our team thoroughly analyzed the traditional emergency service dispatch methods in many nations. We looked at the organizations in charge of running the dispatch centers in each nation, the situations covered, and the emergency contact numbers. We discovered that these systems vary significantly between countries, with some having a single universal emergency number and others having many numbers for various situations. Our research taught us important things about the world's complicated emergency dispatch systems. In addition, it brought attention to the necessity of continuing technological and educational advancements for successful emergency response.

Traditional dispatch systems have supported emergency services for a long time, but several issues have hampered their efficacy. For example, conventional methods rely significantly on human operators to manually acquire and process information, which may be time-consuming and prone to mistakes. This is one of the main problems. In addition, response times may also be impacted by dispatch centers' need for access to real-time data on things like the whereabouts of emergency services, traffic patterns, and weather alerts. Traditional dispatch systems have, therefore, frequently needed help to deliver an effective and efficient emergency response, underlining the necessity for continuous technological advancements and training to increase their capabilities.

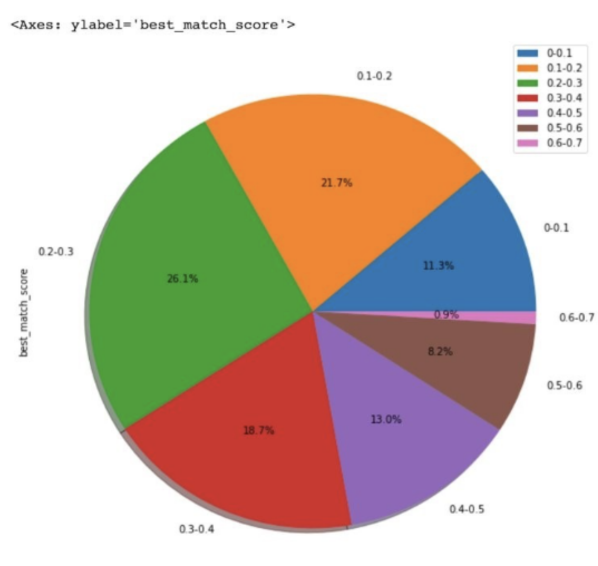

Fig. 5. FuzzyMatcher address mapping results

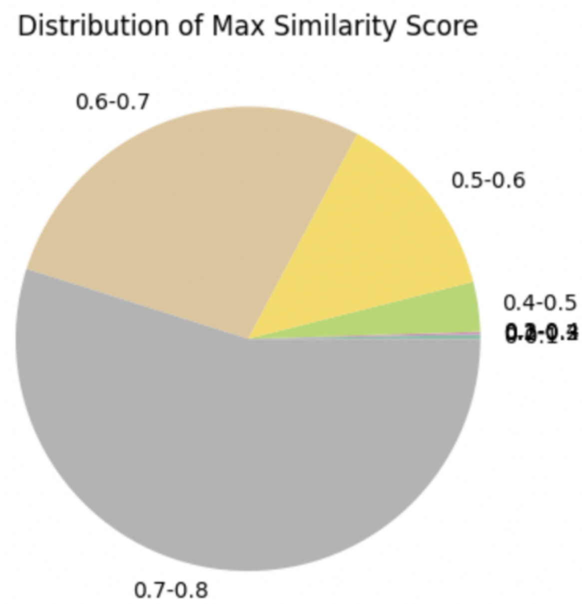

Fig. 6. Distribution of Max Similarity score

Our team extensively studied innovative methods and tools used to boost the effectiveness of conventional emergency service dispatch systems. We discovered several advancements had been made, allowing operators to acquire and analyze information more precisely and rapidly. Examples include Computer-Aided Dispatch (CAD) systems, GPS tracking, and mobile data terminals. Additionally, some dispatch centers have adopted data analytics and artificial intelligence (AI) technologies to analyze real-time data, spot patterns, and anticipate emergencies, which can aid operators in making wise decisions and quickly dispatching the necessary emergency services. Our study emphasizes the significance of dispatch system innovation and enhancement to raise the efficacy and efficiency of emergency response.

Traditional emergency service dispatch methods have transformed with computer-aided dispatch (CAD) technologies. CAD systems integrate real-time data from numerous sources and provide it to operators in a user-friendly interface to automate and expedite the dispatch process. As a result, operators can acquire and evaluate information swiftly, come to wise conclusions, and immediately deploy the necessary emergency services. CAD solutions are anticipated to speed up responses, reduce mistakes, and boost dispatch centers' general effectiveness. Even though CAD systems have some drawbacks, like the requirement for constant upkeep and updates, they have been proven to be an effective tool for enhancing conventional dispatch systems' capabilities.

Since their debut, computer-aided dispatch (CAD) systems have substantially developed, integrating cutting-edge features and technology to improve their functionality. Early CAD systems were created to speed up operations and automate dispatching procedures. Even so, modern CAD systems combine real-time data from several sources, including sensors, mobile data terminals, and GPS

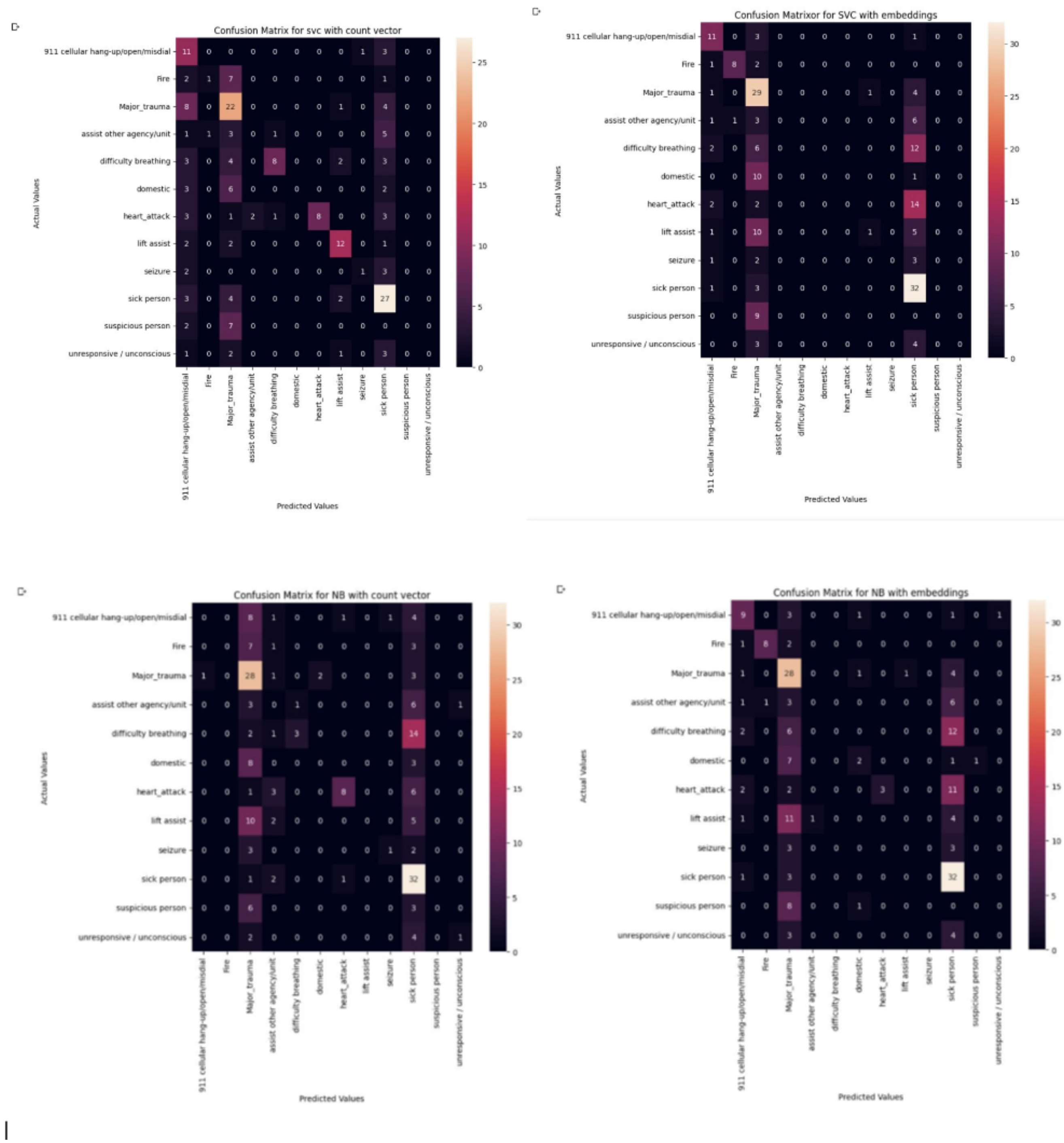

Fig. 7. Confusion Matrix for SVM and NB without Hugging face key-words

tracking, to give operators more precise and timely information. The most current CAD systems also use AI and machine learning algorithms to analyze data, spot trends, and anticipate problems, further enhancing the efficacy and efficiency of emergency response.

Traditional dispatch and CAD systems rely heavily on human involvement, leading to potential errors. A shortage of experienced staff and tedious workload further impact dispatch efficiency. Our

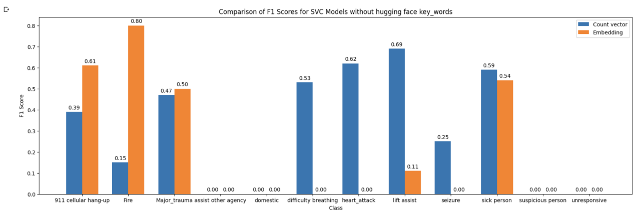

Fig. 8. Comparison for SVM

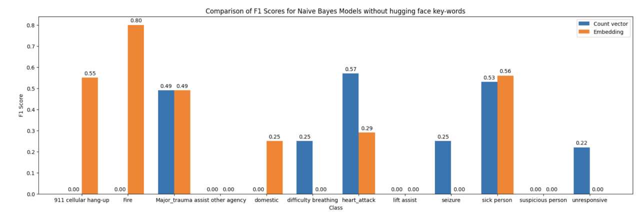

Fig. 9. Comparison for NB

real-time model improves dispatch efficiency by assisting the dispatcher in identifying the patient's condition and dispatching appropriate services with minimal human intervention.

6 METHODOLOGY

The main goal of our team is to develop a supervised machine-learning model that takes the text files as input and outputs a label to the text file based on the conversation between the caller and the 911 operator by the end of the semester.

We broke this main goal into sub-parts to work on so that we can keep developing and improving these sub-parts and add these changes to the pipeline.

The "`Fig.1.`" shows the sub-modules the project is divided into.We keep a continuous check on how the entire model reacts to these changes and decide whether they are a good fit for the entire model.

Some of the sub-goals are:

- Obtaining more data to train our model better.
- Processing the data by removing noise, getting better transcripts, obtaining a better address matching.
- Going through many models and understanding which works best for the project.
- Working towards building a real time model which takes the audio as input and outputs a label.

7 BASELINE MODEL

A simple baseline model has the steps as shown in "`Fig.2.`". The steps involve:

- 1) Converting audio to text: To decode and understand the relation between the call and the target variable, it is essential to convert the calls into text format.
- 2) Extracting address: We have two datasets: the audio calls and the EMS dataset. Unfortunately, both datasets are not linked to each other. Hence, the only way to merge these two datasets is to connect the address in the EMS dataset to the address extracted from the audio. Every 911 operator must inquire about their address; hence there is a high chance of extracting the address from the audio calls.
- 3) Linking the audio files and EMS data: After extracting the address from the audio calls, we need to link the two datasets using the similarity between addresses. Methods like fuzzy linkage, record linking, cosine similarity, and KNN are used to complete the step.
- 4) Cleaning the text: In the first step of building the machine learning model, it is essential to clean the text. The text is converted to lowercase letters, then the Unicode and the stop words are removed.
- 5) Training the model: The clean text is then used to train the classifier model and classify the text into a specific category.
- 6) Testing the model: The model is then tested to analyze how well it is performing.

8 IMPROVED MODEL

The "`Fig.3.`" shows each step involved in the improved methodology.

- a) Speech-to-Text conversion: The audio calls were initially cleaned to remove noise, then some hugging face models for speaker-diarization and segmentation are used to distinguish between the caller and the 911 operator. The audio is then converted to text using Whisper.
- b) Address Extraction: For extracting addresses from the text, the NLTK library is used, and then the extracted address is divided into different parts like state, street, etc.
- c) Dataset Linking: KNN over cosine similarity links the audio calls and the EMS dataset using the address column. KNN algorithm is used to find the 5 nearest neighbors for the addresses in the EMS dataset in the extracted addresses. Then the cosine similarity indexes for the five nearest neighbors are found. Finally, the address with the highest similarity index is selected as the linked address for the EMS data.
- d) Model Building:
- 1) Category consolidation: The EMS dataset consists of a column nature. This column is filled as soon as the medical team reaches the location and tests the patient. Nature is the first impression, and it is the target output. The total number of categories in the target variable is very high. Hence, we need to consolidate them to avoid class imbalance. The classes are reduced based on medical terminology; at last, 12 categories were finalized. The percentage distribution of each of these categories is shown "`Fig.4.`".
- 2) text cleaning and vectorization: As discussed earlier, the text is cleaned by converting it into lowercase and removing all the stopwords and Unicode. After cleaning the text, it is ten vectorized. Two different ways were used to vectorize the text to see which works best for the model. The first method is the count vectorizer, and the second is embeddings. Count vectorizer converts the text into a vector by assigning a number to a word because of how many times it is repeated in the entire text, whereas embedding deals with the word's meaning in the sentence.

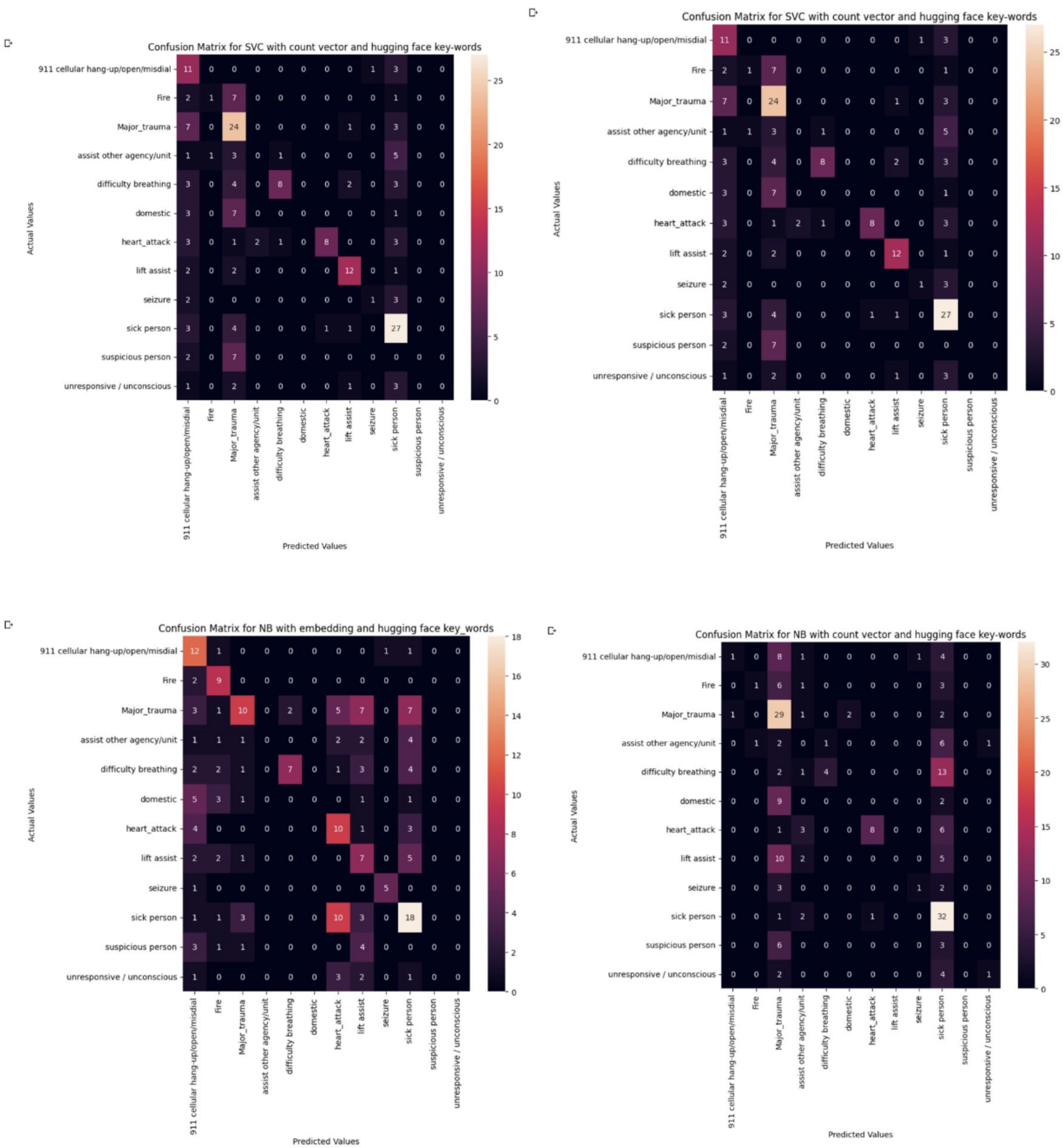

Fig. 10. Confusion Matrix for SVM and NB with Hugging face key-words

- 3) Hugging face keywords: The "en-ner-bc5cdr-md" model is a named entity recognition (NER) model for the English language. Specifically, it is trained on the biomedical domain using the BioCreative V Chemical Disease Relation (BC5CDR) corpus, which consists of over 1500 PubMed articles annotated for chemical and disease entities and their relationships.

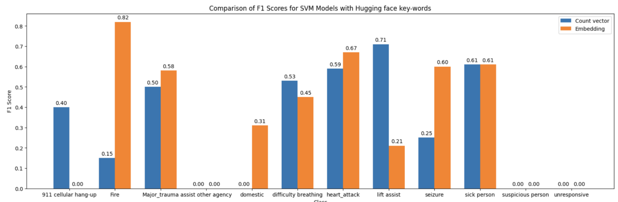

Fig. 11. Comparison for SVC

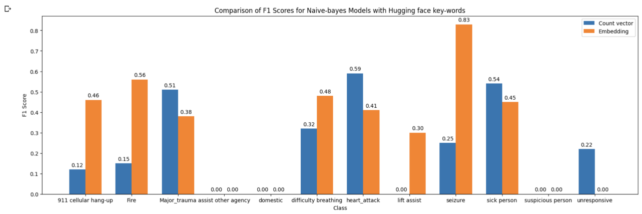

Fig. 12. Comparison for NB

The model is pre-trained on a large corpus of biomedical text and can be fine-tuned on specific tasks and domains as needed. The model is used to extract two different columns to the data set: Key-words-chemicals Key-words-disease

- 4) Training the model: SVC and NB classifiers are used for the supervised classification task. The models are trained only with the vectorized text without hugging face keywords. Both kinds of vectorizations are used to decide which performs the best. In the same way, the models are also trained with hugging face keywords with count vectors and embeddings to compare the performance.

9 DATA PREPROCESSING AND ADDRESS MATCHING:

We have two datasets:

The first dataset contains all audio files.

The second dataset is the EMS dataset.

Our primary objective is to align the audio files with their corresponding "First Impression" data in the EMS dataset. We will do this by mapping the text converted audio files to their corresponding addresses in the EMS dataset.

Following are the steps involved in the alignment process:

Extract the addresses from the audio to text converted files.

Match the extracted addresses to the addresses in the EMS dataset.

Create a map between the audio files and the "First Impression" data in the EMS dataset.

Once the alignment process is complete, we will have a dataset that contains all of the audio files and their corresponding "First Impression" data.

We used two different methods to perform dataset mapping: FuzzyMatcher and KNN with cosine similarity index. The pie charts below show the results obtained by each method during the address mapping process. FuzzyMatcher is a fuzzy matching algorithm that compares two strings and returns a score that indicates how similar they are. KNN with cosine similarity index is a machine learning algorithm that predicts the class of a new data point by finding the k most similar data points in the training set and using their classes to predict the class of the new data point.

FuzzyMatcher address mapping results are shown in“`Fig.5.`” and KNN + Cosine similarity address mapping results are shown in “`Fig.7.`”

After analyzing the results, Cosine Similarity was found to perform better than FuzzyMatcher. With the address mapping, every audio call got linked with the nature from the EMS dataset which will be used for model training in the next step of the project.

10 CORE RESULTS

Project’s objective is to create an entire pipeline that would help dispatchers at 911 centers analyze calls and make decisions. Data collecting, data preparation, audio-to-text conversion of 911 calls, comprehending the datasets for address mapping, first impression detection, and model training were some of the processes in the research and development process. Our goal is to reduce the workload on dispatchers by developing an automated pipeline that would track and examine each incoming call at the 911 center in order to forecast the first impression based on the caller’s tone and linguistics. First the audio to text conversion of the calls was performed with the help of whisper model. This textual data is preprocessed and cleaned to extract the addresses for the incident and to pass as input to the prediction model. To do so, we focused on a variety of categories, including "sick person," "major trauma," "difficulty breathing," "heart attack," and "lift assist," among others, for training of the model to predict the first impression of the call. For initial impression prediction, SVM and Naive Bayes models are currently being used. To increase the semantic data provided to the model we used the hugging face model "en-ner-bc5cdr-md"(named entity recognition (NER) model for the English language). Using Hugging Face to extract the data from the "en-ner-bc5cdr-md" model, we added clinical and disease-related keywords in addition to textual audio calls.

Additionally, we worked on matching the EMS dataset with the addresses extracted from 911 call audio to text conversion. We used three distinct techniques: KNN + Cosine Similarity index, Cosine Similarity, and FuzzyMatcher. Even though it was challenging to validate the model output in the absence of any ground truth, we manually assessed the results for six months of data. After analyzing the outcomes, we discovered that Cosine Similarity with KNN outperformed FuzzyMatcher and Cosine Similarity index, matching 54.9 percent of addresses with an index of 0.7 to 0.8, 27 percent of the addresses are with 0.6 to 0.7 cosine similarity index and so on. For improved outcomes, we want to continue to enhance the address extraction process.

The initial confusion matrices and scores for SVC and NB without hugging face key-words for both count vector and embeddings are as shown in “`Fig.8.`”

F1-score comparison for SVC without hugging face key-words for count vector and embeddings are shown in “`Fig.10.`”

F1-score comparison for NB without hugging face key-words for count vector and embeddings are shown in “`Fig.11.`”

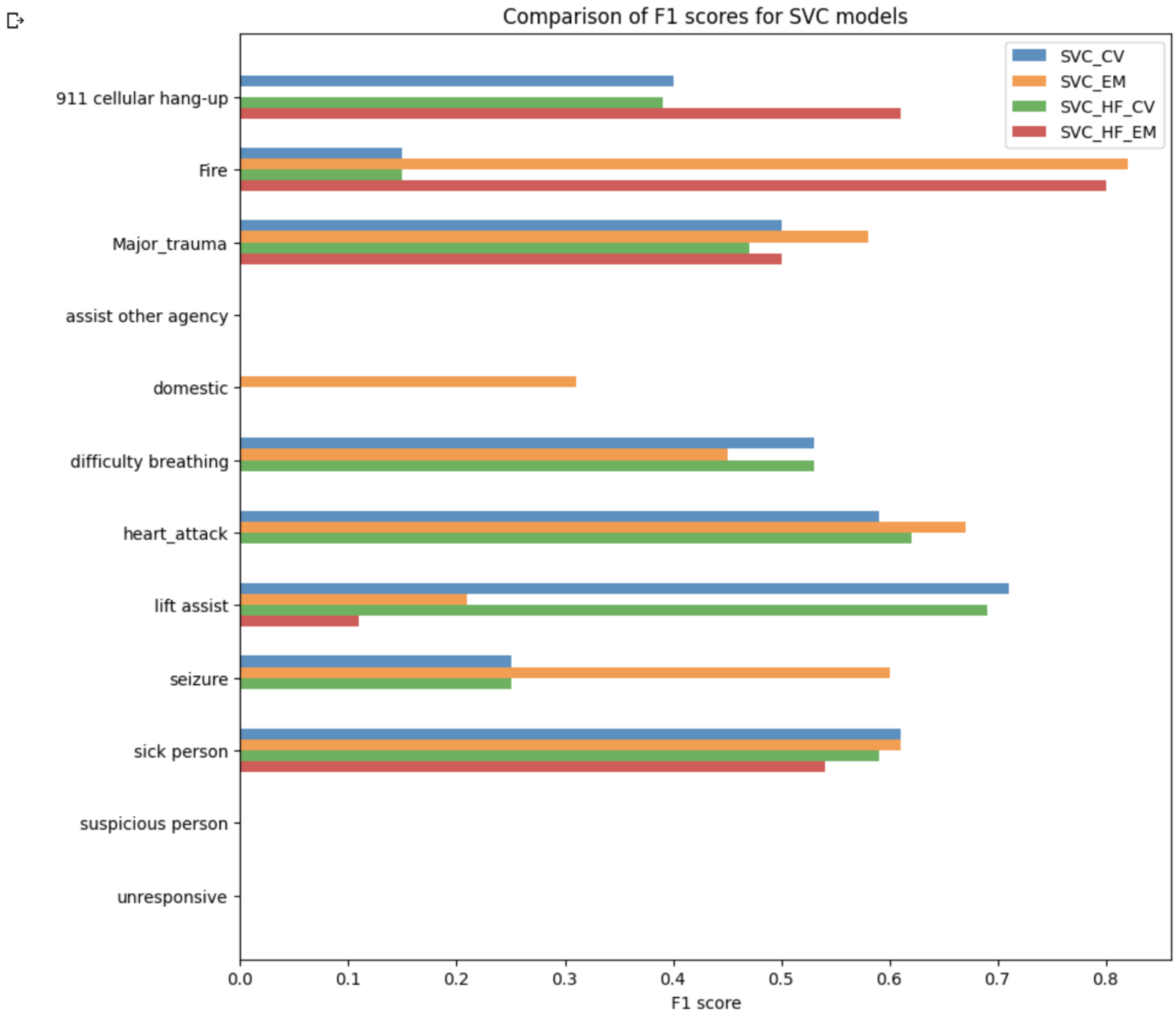

Fig. 13. Comparison of F1-SCORES FOR SVC MODELS

The initial confusion matrices and scores for SVC and NB without hugging face key-words for both count vector and embeddings are as shown in "`Fig.9.`"

F1-score comparison for SVC with hugging face key-words for count vector and embeddings are shown in "`Fig.12.`"

F1-score comparison for NB with hugging face key-words for count vector and embeddings are shown in "`Fig.13.`"

F1-score comparison for SVC with and without hugging face key-words for count vector and embeddings are shown in "`Fig.14.`"

F1-score comparison for NB with and without hugging face key-words for count vector and embeddings are shown in "`Fig.15.`"

By comparison of different results, we conclude that both the SVC and NB models perform the same on the dataset.

There is an improvement when embeddings are used instead of count vectors.

Even though the f1-scores improve drastically for certain categories after using hugging face key words, the f1 score remains zero for some categories due to class imbalance.

11 DISCUSSION

11.1 Hypothesis Validation

This study hypothesized that the implementation of natural language processing techniques in the analysis of 9-1-1 calls will enable the development of a machine learning model that can improve the efficiency of 9-1-1 care centers, leading to the dispatch of accurate resources and real-time decision-making support for dispatchers. Currently we are able to build entire pipeline for this. Each section

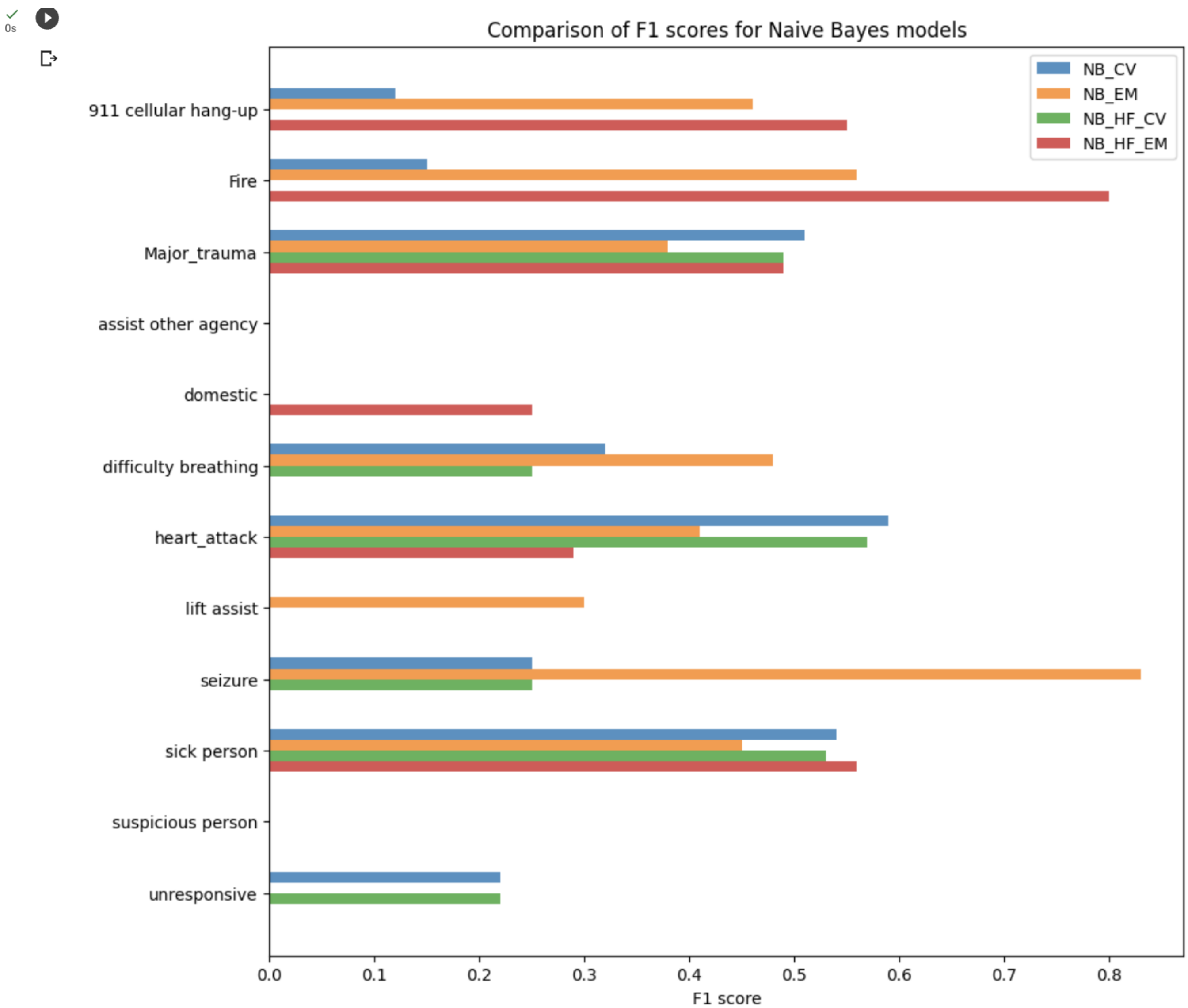

Fig. 14. Comparison of F1-SCORES FOR NB MODELS

in the pipeline is performing as per expectations and we are working on improvements of results and its automation. Once automated, it is likely that the model will be able to correctly classify the calls and improve the efficiency of 9-1-1 care centers. Hence, the hypothesis provided initially underlines the work and system built in the project.

11.2 Risked Assessed

There were several risks that were addressed when completing this project. One of the risks was the potential for inaccuracies in the audio-to-text conversion. While Whisper can minimize these errors, it cannot get rid of them completely. Due to the nature of the calls, it can often be difficult to understand what is being said, especially through Natural Language Processing. Some contributing factors are language barriers, mental and emotional states of the callers, and audio quality. An error in the processing of the audio can propagate into errors with classification and must be addressed accordingly. Another risk is the potential for the incorrect classification of calls, which could have serious consequences for the patients involved. Instead of increasing efficiency, misclassifying a call could cause confusion and slow down the dispatchers. This would delay the arrival and delivery of care. Due to the nature of Emergency Medical Services, this is a risk that cannot be taken lightly. If the proper care isn't taken to address these concerns, people's lives could be at stake.

These risks were addressed by requiring the aid of human dispatchers. This real-time machine learning system is not meant to make decisions independently. Instead, it is meant to act as a resource to assist dispatchers in determining the correct emergency services needed. Therefore, dispatchers should be able to catch and prevent errors caused by audio-to-text inaccuracies as well as classification errors before they are able to disrupt the quality of care. Additionally, another goal of this project is to create a scoring system to measure the quality of the dispatcher's decision-making process. This will ensure that the technology continues to improve to reduce the likelihood of such errors.

Furthermore, there were concerns the time constraints placed on the project would not allow it to be completed. This issue was addressed with the presence of other members of the team with a longer time frame. Their ability to continue the work once the semester ends will ensure that the project is completed, and the hypothesis is tested and validated.

11.3 Deliverables for Dissemination

The biggest deliverable of the project was creating the end-to-end pipeline. This task was broken into sub-parts that were continuously updated to keep improving the project and adding the changes to the pipeline. These subparts included collecting the data set to work with. It also included processing the data by removing the noise, getting better transcripts, and obtaining a better address mapping. Additionally, many models were analyzed to understand which worked best for the project. These subparts were then connected to make a better output model.

12 CONCLUSION

In conclusion, during the project we worked on creating an end-to-end pipeline to support call analysis and decision-making for dispatchers at 911 centers. Data collection, data preparation, audio-to-text translation of 911 calls, address mapping, first impression detection, and model training were some of the phases in the pipeline. To lessen the workload on dispatchers, the goal is to develop a fully automated system that could monitor and handle incoming calls at the 911 center, predicting the first impression based on the caller's tone and linguistics. We worked on SVM and Naive Bayes models to employ the initial impression prediction. A comparative study of the outcomes provided by both the models was performed along with analyzing the impact of providing additional support by extracting clinical keywords with hugging face model.

We also used a variety of methods to match addresses taken from 911 calls to the EMS dataset, and after manual evaluation, we discovered that Cosine Similarity with KNN performed better than the other approaches. For better outcomes in the future, we will keep working to enhance the address extraction procedure. Overall, the research has produced encouraging results and holds great promise for improving dispatchers' job at 911 centers.

13 FUTURE SCOPE

- Continue to enhance address extraction process
- Obtain more data to help train the model better
- Build a real time model
- Apply the model at a dispatch centre
- Create a scoring system to measure the quality of the dispatcher's decision-making process

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