AN EMOTION DETECTION MOBILE APPLICATION TO DECREASE POTENTIAL MENTAL DISORDER AMONG SENIORS USING SENTIMENT ANALYSIS FROM AUDIO DATA

Tengjie Qiu[1], Daniel Carter[2]

[1]Mater Dei High School, 1202 W Edinger Ave, Santa Ana, CA 92707
[2]Computer Science Department, California State Polytechnic University, Pomona, CA 91768

ABSTRACT

We wanted to create a better, more trustworthy solution for caretakers to determine the emotion and feelings their patients are experiencing. This is useful for caretakers to adjust how they go about caring for their patients.

To solve this, we decided to create a mobile consumer application. Architecturally, the user (caretaker) will be using this mobile app as a front end which will record and send audio of the patient to a backend service. The service will be hosted on AWS and it will be a sentiment analysis algorithm written in Python. The service will analyze and determine the feeling of the patient and send it back to the front end for the caretaker to see. The front end was written in Flutter.

To evaluate the effectiveness of the proposed mobile application, we conducted testing focused on two key aspects: accuracy and response speed. The accuracy of the sentiment analysis algorithm was assessed by comparing the analysis results of pre-recorded audio with predetermined feelings. This evaluation aimed to measure the algorithm's ability to correctly identify and classify emotions. Additionally, we tested the speed of response by sending audio samples of varying lengths, ranging from 2 seconds to 60 seconds. The objective was to determine the optimal response time for providing feedback on the user's mood. Our findings revealed that the algorithm demonstrated high accuracy in detecting emotions within the tested audio samples. Moreover, the ideal response time for generating feedback was identified as 5 seconds, striking a balance between promptness and accuracy. These testing results validate the efficacy of the proposed application in accurately analyzing sentiment and providing timely responses, supporting its potential as an effective tool for monitoring and addressing the mental well-being of elderly individuals.

This proposed mobile app, utilizing sentiment analysis, offers a convenient and accurate means of monitoring and addressing the mental well-being of elderly individuals. Its potential to combat loneliness and provide timely support makes it a valuable tool for improving their overall quality of life.

KEYWORDS

Sentiment Analysis, Audio Data, Mobile Application, Mental Disorder

1. INTRODUCTION

Although the concept of mental health has been emphasized among adults and adolescents, the mental well-being of senior citizens often seems to be overlooked. While society recognizes the importance of mental health, there are still existing risk factors that contribute to mental disorders

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among the elderly [1]. Family factors play a crucial role in the lives of older adults, and studies have shown a higher morbidity rate of borderline disorder associated with loneliness, low self-esteem, and a loss of life purpose [4]. Research on a sample of low-income residents in a medium-sized northeastern city revealed that 26% of the population reported major depressive disorder, highlighting the prevalence of mental health issues among seniors [2]. The COVID-19 pandemic has further exacerbated these issues, as the self-isolation and quarantine measures impose significant psychological stress on seniors [5]. Professional studies consistently emphasize the correlation between mood and overall well-being in older adults, underscoring the seriousness of mental illness in this population [14]. For instance, studies have shown that elderly individuals with mood disorders tend to have lower height, weight, and diastolic pressure [6]. This suggests a direct correlation between mental disorders in the elderly and their physical health. It is important to prioritize the examination and treatment of depressed elders to mitigate the risk of adverse outcomes, such as inflammation [7]. These findings highlight the urgent need to address mental health issues in the elderly population, especially considering the risk factors and the impact of the COVID-19 pandemic. By recognizing the correlation between mental and physical health in older adults, we can work towards providing better care and support for this vulnerable demographic.

Methodology A, conducted by Wong and Ujimoto, aimed to investigate the mental health of Asian elders during the assimilation process after migration [8]. They focused on the role of resilience and coping mechanisms, particularly within the context of cultural heritage, to identify factors that affect the mental health of Asian American elderly. The researchers emphasized that resilience plays a crucial role in helping elders overcome the stress caused by cultural differences. However, they acknowledged the limitations in building resilience, as it heavily depends on the availability of coping resources such as social support from friends, family, and ethnic communities. The authors highlighted the importance of considering the time and resources required for implementing coping mechanisms for potential mental health issues.

Methodology B, led by Tai-Seale and his team, examined the care provided to elders with mental disorders during doctor visits using video recordings. Their findings indicated that only a small percentage (approximately 22%) of topics discussed during these visits focused on mental health. The researchers emphasized the need for systematic interventions and guidelines to address mental health issues during doctor visits for elderly individuals [15]. However, the limitation of this solution lies in the fact that elders may not freely discuss their mental well-being in such settings, which raises concerns about the effectiveness of identifying and addressing mental health issues solely through doctor visits [12].

Methodology C, presented by MacCourt and Tuokko, introduced the Seniors Mental Health Policy Lens (SMHPL) as a tool to reflect the values and perspectives of older adults regarding their mental health. The SMHPL was designed to provide policy makers with an overall view of the mental health needs among seniors, aiding in the identification of relevant issues. However, the authors overlooked the potential time required for the government to successfully identify and address these issues using SMHPL. Furthermore, while SMHPL contributes to improving social awareness, it may lack effectiveness at the individual level in terms of providing timely and targeted support for mental health concerns [13].

In order to address the mental health problems among the elderly individuals, the solution being proposed by this report is the creation of a mobile application that utilizes sentiment analysis to provide feedback regarding the current mood of the speaker. Checking the mood of elders in daily pattern could prevent the potential isolation that they may feel, especially since “older people, particularly those over 80, seem more reluctant to seek treatment for psychological disorders” [11].

This application enables the users to examine and check-in seniors' mood based on the tone of their voices. In other words, the application offers a convenient and accurate way to determine the mood of the seniors.

There is an added benefit to incorporating an electronic device and assistant. For instance, it enables the collection of daily data of the elderly people which could be effectively stored and analyzed by professionals to examine the possibilities of potential mental illness. Being able to digitally track and analyze this data can aid a lot of other operations in a hospital or care center. For example, the interactions between the elders and users that occur could possibly eliminate the loneliness and isolation that older adults may feel. Furthermore, the daily examinations of the mood would help the users to be earlier to identify potential mood disorders. Supporting this perspective, a study aimed to examine the need of mental services among elders found the resolving of unmet mental health needs among elders, such as interpersonal relation, social support, and socialization could prevent mental issues [9].

On the other hand, people understand the emotion of others through two aspects controlled by parts of the brain: The semantic knowledge about the emotion and the causes of certain emotion [10]. Utilizing a mobile app and sentiment analysis algorithm could also minimize the bias made by our brain, preventing users from making assumptions on the mental state of their patients or family members.

Overall, with the help of this application, users could effectively determine the mental state of elderly people eliminating their potential bias through technological aid. The examination also provides the opportunity for users to discover the mental illness in the earlier state.
Section 4 involved two experiments that were mainly testing the effectiveness of our sentiment analysis algorithm. The first Experiment was testing the accuracy and strictly just the accuracy of the algorithm. The data set we used for this was 10 audio recordings with a corresponding pre set expected output that will be the expected feeling. In order to make sure the only thing that is tested is the accuracy of the algorithm, all recordings are going to be at a constant 4 seconds. The most common response was the expected response however, it is on average only 60% of the time. This means the algorithm could be improved as this is not more accurate than humans.

The second experiment was to determine the ideal audio length. This is to make sure the user has a good experience and doesn't wait too long for a response. Strictly the response time was being tested so recordings ranging from 3 to 60 seconds were used. The results showed that the longer the recording the longer it took for the response. 3-10 second long recordings were kept at a reasonable response time and we decided that 5 seconds is ideal in terms of response time as well as accuracy.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Interpret the tone

One important part of a program that measures sentimentality in voice input is the way it analyzes the tone and pitch of the voice. A possible challenge that could come up is that the algorithm might not correctly interpret the tone or pitch of the voice, leading to inaccurate sentiment analysis. To address this, you could use multiple algorithms and compare their results to improve accuracy. Another problem could be that the quality of the recording itself isn't good enough, making it hard to analyze the tone and pitch accurately. To fix this, the program could use noise reduction techniques or suggest that the user re-record with better audio quality. Using multiple algorithms and noise reduction techniques could help improve the sentiment analysis accuracy in voice input.

2.2. The menu items

A major component of our program's UI design would be the menu system. We need to consider potential problems that could arise when implementing this component and how we could address them. One issue could be with the clarity of the menu items. If the menu options are not clear, users may have difficulty navigating the app and finding the information they need. To resolve this, we could use concise and descriptive labels for each menu item and provide visual cues to help guide the user. Another issue could be with the organization of the menu items. If the menu items are not organized in an intuitive manner, users may become frustrated and confused. To address this, we could group related items together and organize them in a logical sequence. By taking these steps, we can ensure that our app's menu system is easy to use and understand for all users.

2.3. The length of the audio

Besides the parts that are previously mentioned, the length of the recorded audio may also lead to a concern about the application. In other words, if the audio being recorded is short, the sentiment analysis lacks enough data to report an accurate solution. Afterall, the accuracy of the application should be prioritized. Meanwhile, if the user records the audio longer than the expectation, the data would take a wait time in order to be transmitted. To resolve this potential issue, we could conduct an experiment and aim to determine the shortest recording with enough data for sentiment analysis to examine.

3. SOLUTION

This application is being written in the Flutter framework, an open-source UI software development tool kit. The application itself is being programmed in Dart since that's the language Flutter is built with. In general, there are three major components that are essential to this program: login in/sign out, adding patient list, and audio analysis. This program is designed to be available for users to download free on their devices. As the users open the application on their mobile devices, the splash screen would first be shown. Then, the application directs the users to the login screen. If the user does not have an account for the application, the user could click the sign up bottom and create an account with their email and appreciate passwords. Furthermore, once the user successfully login their account, the application would display the list of patients/family members that have been previously saved if applicable. On this page, the user could also choose to add a patient/family member by pressing the "+" bottom. In order to proceed with the functionality of the program, the user could select a member from the list and enter the chat page. In other words, the chat page of this particular patient/family member offers the opportunity to record the audio of that patient. After the recording is done with a brief wait time, the result processed by the sentiment analysis reports the type of emotion being found, which displays on the screen. Based on the audio being recorded, the results could be neutral, happy, sad, or ect.

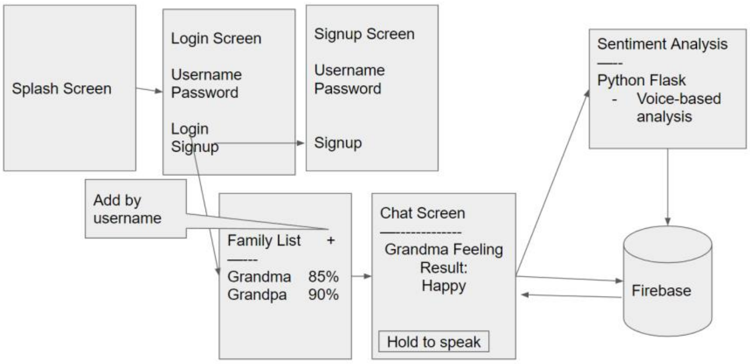


Figure 1. The overall flow chart of the application

The account credentials of the user is being stored in a database, called Firebase when the users first signup for this application. The credentials include the users' email, passwords for the account, and a unique UID to identify the users. Once the user successfully signs up for an account. They could use their credentials to login their account.

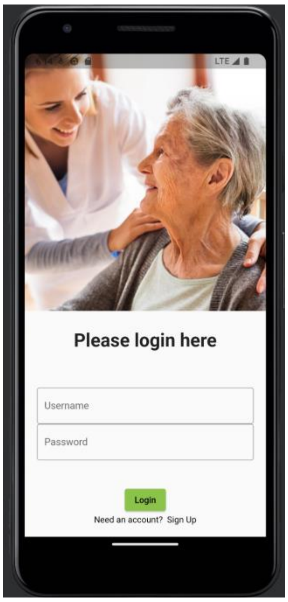


Figure 2. The login page of the application

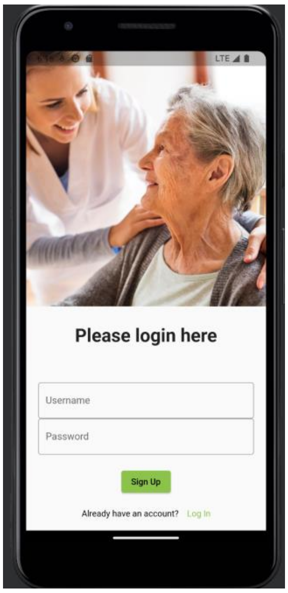


Figure 3. The signup of the application

```
Container(
  margin: EdgeInsets.all(20),
  child: Column(
    children: [
      TextField(
        controller: emailController,
          decoration: const InputDecoration(
            border: OutlineInputBorder(),
            labelText: 'Username',
          ) // InputDecoration
      ), // TextField
      TextField(
        controller: passController,
            obscureText: true,
            decoration: const InputDecoration(
            border: OutlineInputBorder(),
            labelText: 'Password'
          ) // InputDecoration
      ), // TextField
    ],
  ) // Column
), // Container
```

```
Future signIn() async {
  await FirebaseAuth.instance.signInWithEmailAndPassword(
      email: emailController.text.trim(), password: passController.text.trim());
}
```

Figure 4. The code sample for the users to type their account credentials

The code sample shown in Figure 4 is the representation of the login/sign up functionality of the program. This section of the code is being applied after the splash screen of the application is being displayed. With the method, signIn, being used to verify the correctness of the account credential, this selection of the code provides the text field for the users to enter their account information. The labelText is being used to indicate to the user about the information that they should input. Furthermore, the controllers, emailController and passwordController, are used to create data streams with Firebase, where the user credentials are stored. As the user input their credentials, these variables could make a connection between the application and the database with the method shown in figure 4. If the password that is entered in the text field exists in the database and matches with the corresponding email address, the program would display the Patient List page.

As Figure 5 and Figure 6 shown below, the main page of the application is a list of Patient/Family members on the screen. These unique account information are stored in the Firebase database under each account. Since these account data is saved on the cloud, these data would not be lost once the account is being logged out. Furthermore, a widget is being included in this UI that is used to add new Patient/Family members into the list. The general information about these Patient/Family members is needed for them to be added into the list shown in the main page.

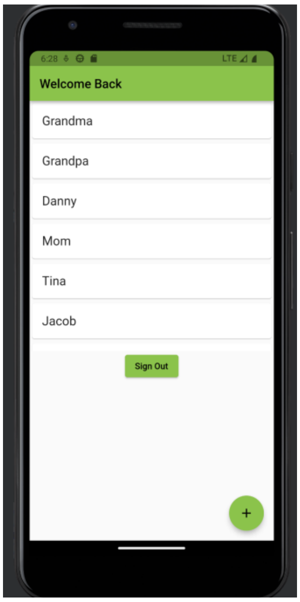
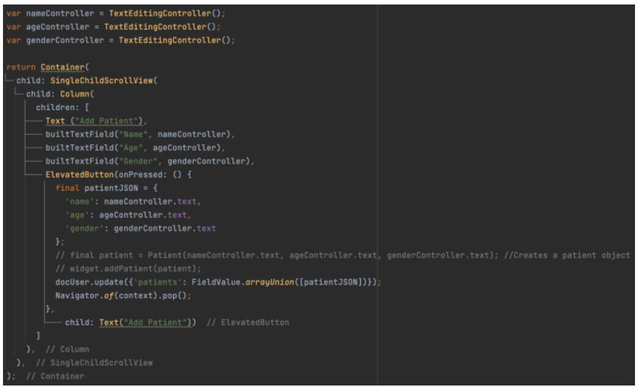


Figure 5. The page where the list of Patient/Family members are stored

Figure 6. The widge that could be used to add Patient/Family members



```
var nameController = TextEditingController();
var ageController = TextEditingController();
var genderController = TextEditingController();

return Container(
  child: SingleChildScrollView(
    child: Column(
      children: [
        Text ("Add Patient"),
        builtTextField("Name", nameController),
        builtTextField("Age", ageController),
        builtTextField("Gender", genderController),
        ElevatedButton(onPressed: () {
          final patientJSON = {
            'name': nameController.text,
            'age': ageController.text,
            'gender': genderController.text
          };
          // final patient = Patient(nameController.text, ageController.text, genderController.text); //Creates a patient object
          // widget.addPatient(patient);
          docUser.update({'patients': FieldValue.arrayUnion([patientJSON])});
          Navigator.of(context).pop();
        },
          child: Text("Add Patient"))  // ElevatedButton
      ]
    ),  // Column
  ),  // SingleChildScrollView
);  // Container
```

Figure 7. This code sample show the functionality of adding a patient/family member

The code selection shown in Figure 7 carries out the functionality of adding data in the list. The Container in the code selection represents the widget shown in Figure 6. This code requires the users to enter three basic information about the patient/family member that they are trying to add: Name, Age, and Gender. These three input values are later saved in variables sent to the database. After the user has pressed the “Add Patient” button, the patient/family members would appear on the main page for users to start recording their audio.

Furthermore, one of the most important components of this application is the audio recording and sentiment analysis. Figure 8 shows the UI for the recording page of the application. When the user presses the green microphone icon, the page would start to record through the microphone of the device. Once the recording begins, the patient/family member should start talking into the device. After a brief period, the user should stop the recording. The audio being recorded would be sent to Amazon Web Services (AWS), where the sentiment analysis is located. Then the audio is processed by the analysis and the result would be returned.

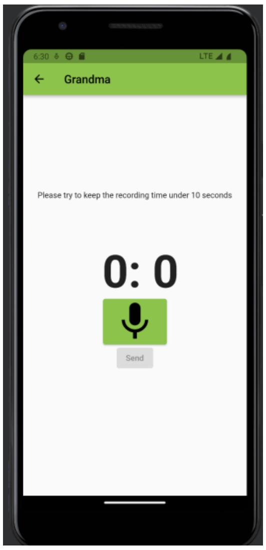


Figure 8. The recording page for each patient/family member

```
Future<void> sendAudioFile(String filePath) async {
  //https://Jays-Feeling-App.danielcarter25.repl.co/analyze
  final url = Uri.parse('http://52.53.254.134:5000/fetch_prediction');
  final request = http.MultipartRequest('POST', url);
  request.files.add(await http.MultipartFile.fromPath(
    'audio',
    filePath,
    contentType: MediaType('audio', 'wav'),
  ));
  final response = await request.send();
  final responseBodyBytes = await response.stream.toBytes();
  final responseBody = utf8.decode(responseBodyBytes);

  if (response.statusCode == 200) {
    print('Uploaded successfully');
    setState(() {
      _response = responseBody;

      _isRecordingDone = false;
    });
  } else {
    print('Upload failed: ${response.statusCode}, Response: $responseBody');
  }
}
```

Figure 9. The code sample performs the functionality of processing the sentiment analysis

The selection of code shown in Figure 9 would be used when the recording of the audio is being completed. The method, sendAudioFile, represents the process of sending the audio file to the sentiment analysis located at AWS. The variables, url and request, are used to request the server for the result of analysis of the analysis. Furthermore, this method also checks if the upload is successful. By comparing the status code, the method would report if the audio is being uploaded or the upload failed. As previously mentioned, AWS served as the storage for the sentiment analysis. While saving the analysis in a cloud, the program would be more efficient and lower the risk of function failure. After the analysis for recording is complete, a feedback would be sent back to the program, which is later being displayed on the recording page of the application.

4. Experiment

4.1. Experiment 1

One possible blind spot when testing a program that measures sentiment analysis is the potential bias in the training data, which can result in inaccurate sentiment classification for certain demographics or cultural contexts. It is important for the program to work well in order to provide fair and unbiased sentiment analysis results that are applicable to a diverse range of users.

To ensure the accuracy of the sentiment analysis, a systematic testing approach will be employed. The testing procedure will involve utilizing a pre-set dataset comprising audio recordings, each associated with a specific emotion. For instance, if an audio clip exhibits a happy tone, it will be labeled with the corresponding happy emotion. Subsequently, these audio files will be subjected to the sentiment analysis algorithm, and the generated results will be compared to the expected emotions. This process will be repeated for a sample of five recordings, allowing for a comprehensive assessment. By calculating an average from the obtained results, we can gauge the performance and accuracy of the sentiment analysis program. This testing methodology helps validate the reliability of the program in accurately detecting and classifying emotions in real-time data.

Constant: Recording length is 4 seconds.

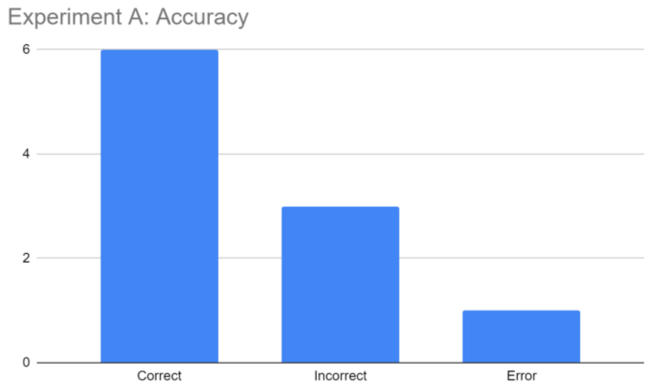


Figure 10. Figure of experiment 1

The results were somewhat surprising, as only 6 out of 10 recordings were accurately classified. This suggests that the sentiment analysis algorithm would benefit from improvements to effectively handle diverse voice characteristics, variations in audio quality, and other potential challenges. Enhancements to the algorithm are crucial to improving its accuracy and dependability.

The primary factor influencing the results is the accuracy of the sentiment analysis algorithm. By enhancing the model's capacity to handle a wider range of voice characteristics, optimizing audio processing techniques, and utilizing high-quality training data, more precise classification outcomes can be achieved.

Expanding the dataset based on the provided averages, we can estimate that out of 100 recordings, approximately 60 would be correctly classified, 30 would be misclassified, and 10 would yield errors. However, it is important to note that these estimations are based on the given averages and may not accurately reflect outcomes in a larger dataset.

4.2. Experiment 2

Furthermore, in the context of a research paper experiment focused on an app that calculates people's sentimentality based on audio files, it is important to address the potential issue of the time required for audio file analysis. The duration of the analysis process may pose a challenge, as users might experience delays or prolonged waiting times for the app to provide sentiment analysis results. This can potentially impact user satisfaction and overall app usability. Therefore, it is crucial to investigate and explore methods to optimize the analysis time, such as employing efficient algorithms, leveraging parallel processing techniques, or utilizing cloud-based computing resources. By reducing the analysis time, the app can deliver prompt and real-time sentiment analysis, enhancing user experience and usability.

To test the time it takes to analyze audio with the sentiment analysis algorithm, we can design a quick experiment. We will select a set of voice recordings of different lengths, ranging from short to long. Times will vary from 3 seconds to 1 minute. Each recording will be sent individually to the sentiment analysis algorithm, and the time taken to process each audio file will be recorded. We will repeat this process for multiple recordings to gather sufficient data. By analyzing the time taken for each audio length, we can identify any patterns or trends in the processing duration.

This experiment will provide insights into the relationship between the length of audio input and the time required for sentiment analysis, enabling us to optimize the algorithm's efficiency and scalability.

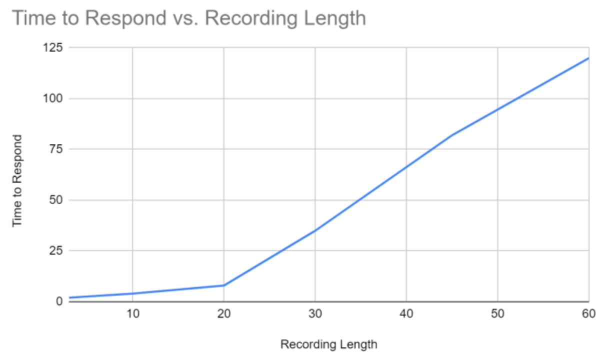


Figure 11. Figure of experiment 2

Upon analyzing the data, we observed that the algorithm exhibited a consistent processing time for shorter recordings. For instance, the sentiment analysis algorithm responded to a 3-second recording in 2 seconds and a 10-second recording in 4 seconds, indicating a relatively low processing time for these shorter durations.

However, as the length of the recordings increased, we noticed a significant increase in processing time. For example, the sentiment analysis algorithm required 35 seconds to process a 30-second recording, 82 seconds for a 45-second recording, and 120 seconds for a 60-second recording. This trend suggests that longer audio files require more computational resources and time for the sentiment analysis algorithm to analyze and determine the sentiment accurately.

The data highlights the need to consider the trade-off between processing time and the desired length of audio input. If real-time or near-instantaneous analysis is crucial, shorter recordings would be more suitable. On the other hand, if accuracy takes precedence over processing time, longer recordings can be utilized, recognizing the increased processing duration they entail.

Further optimization of the sentiment analysis algorithm may be necessary to improve efficiency and reduce the processing time for longer recordings. Techniques such as parallel processing or optimization algorithms can be explored to enhance the algorithm's performance, enabling quicker analysis without sacrificing accuracy.

5. RELATED WORK

Similarly, researchers Wong and Ujimoto aimed to investigate the mental health of Asian elders during the assimilation after migration [8]. They adopted the perspective of cultural heritage and coping mechanisms in order to determine factors affecting the mental health of Asian American elderly [3]. During their investigation of previous literature, they posit the role of resilience among the Asian American elderly provided the essential support after they left their familiar environment. This sort of resistance may help the elders to overcome the stress caused by cultural differences. However, the researchers recognized the limitation in the building of resilience [8]. The authors stated resilience heavily depends on the availability of coping resources. For instance, social resources, such as friends, family, ethnic community, are examples of coping resources. Although resilience offered a chance for the elders to accept stressors earlier, the time and resources required are something that the authors highlighted. This perspective reminded us of the importance of considering the requirement and certain cost that a coping mechanism for potential mental health issues may need.

On the other hand, Tai-Seale and his research team presented this social issue from a different perspective [12]. They investigated the care of mental disorders being given to elders by using videotype during their doctor visits. By analyzing 385 video types with 22% of topics regarding mental health, the research team concluded that doctor visits of elderly should include systematic intervention and guidelines regarding mental disorders. Although this research provides a solution that may help the doctors to identify potential mental health issues, the limitation of this solution is also significant since only 22% of the topics during doctor visits are regarding mental health, suggesting the possibility that the elders would not talk about their mental health.
Additionally, the research conducted by MacCourt and Tuokko introduced the idea of The Seniors Mental Health Policy Lens (SMHPL) to address the senior mental health issue. “The SMHPL was designed to reflect the values and perspectives of older adults regarding their mental health” [13]. The authors posited that SMHPL offers the policy makers an overall view of the mental health needs among the seniors, helping them to identify any issues related to seniors’ mental health. However, the author ignored the potential time needed for the government to be able to successfully identify and address a possible issue. Although SMHPL increases the overall socialware, in terms of individuals, it lacks the effectiveness.

6. CONCLUSIONS

This mobile application is designed to help families and care teams to determine the emotions of particular elders. Still, it consists of a certain level of limitation while pursuing the given goal. In order to secure and store the account credentials of the users, this application utilizes a third-party database, causing the increasing risk of data leak. However, after cautious selection of the databases, we have chosen a well-known database with a high reputation to ensure the user credentials are maintained. Furthermore, while the program analyzes a given audio after recording, users may potentially experience long wait times due to the length of the audio. If we have more time with this project, we would prioritize on improving the user experiences, making this mobile application more user friendly. Thus, more people would feel comfortable using our application in their daily life.

Overall, the mental health of seniors should be highlighted in society. In order to raise awareness of mental illness among the elders , we developed this mobile application using Futter to provide a way to proceed to an early diagnosis. In general, this application has few major components including sentiment analysis, which has been examined for its reliability. Compared with other methodology posited by research teams, this application is more effective in a smaller group of people, suggesting our application could be used in families or elderly houses.

REFERENCES

[1] Kumar, T. Sathis, et al. "Sentimental analysis (opinion mining) in social network by using SVM algorithm." 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC). IEEE, 2020.

[2] Robison, Julie, et al. "Mental health in senior housing: Racial/ethnic patterns and correlates of major depressive disorder." Aging & mental health 13.5 (2009): 659-673.

[3] Carpenter, Brian D., Margaret Gatz, and Michael A. Smyer. "Mental health and aging in the 2020s." American Psychologist 77.4 (2022): 538.

[4] Petrova, N. N., and D. A. Khvostikova. "Prevalence, structure, and risk factors for mental disorders in older people." Advances in Gerontology 11 (2021): 409-415.

[5] Chong, Terence WH, et al. "Mental health of older adults during the COVID-19 pandemic: Lessons from history to guide our future." International Psychogeriatrics 32.10 (2020): 1249-1250.

[6] Tseng, Tzu-Jung, et al. "Association between health behaviors and mood disorders among the elderly: a community-based cohort study." BMC geriatrics 19.1 (2019): 1-14.

[7] Morimoto, Sarah Shizuko, and George S. Alexopoulos. "Immunity, aging, and geriatric depression." Psychiatric Clinics 34.2 (2011): 437-449.

[8] Wong, Paul TP, and K. Victor Ujimoto. "The elderly: Their stress, coping, and mental health." (1998).

[9] Palinkas, Lawrence A., et al. "Unmet needs for services for older adults with mental illness: comparison of views of different stakeholder groups." The American Journal of Geriatric Psychiatry 15.6 (2007): 530-540.

[10] Spunt, Robert P., and Ralph Adolphs. "The neuroscience of understanding the emotions of others." Neuroscience letters 693 (2019): 44-48.

[11] Jones, Rebecca L. "'Older people'talking as if they are not older people: Positioning theory as an explanation." Journal of Aging Studies 20.1 (2006): 79-91.

[12] Tai-Seale, Ming, et al. "Two-Minute Mental Health Care for Elderly Patients: Inside Primary Care Visits: (See editorial comments by Drs. Charles Reynolds, Mario Cruz, Carrie Farmer Teh, and Bruce L. Rollman)." Journal of the American Geriatrics Society 55.12 (2007): 1903-1911.

[13] MacCourt, Penny, and Holly Tuokko. "Development of a seniors' mental health policy lens: An analytical tool to assess policies and programs from a seniors' mental health perspective." Canadian Journal of Community Mental Health 24.2 (2009): 35-53.

[14] Yuliyanti, Siti, Taufik Djatna, and Heru Sukoco. "Sentiment mining of community development program evaluation based on social media." TELKOMNIKA (Telecommunication Computing Electronics and Control) 15.4 (2017): 1858-1864.

[15] Sabariah, Mira Kania, and Veronikha Effendy. "Sentiment analysis on Twitter using the combination of lexicon-based and support vector machine for assessing the performance of a television program." 2015 3rd International Conference on Information and Communication Technology (ICoICT). IEEE, 2015.