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Animind: A Gamified Framework for Emotional Regulation and Mental Wellness using Spring Boot and Heuristic Sentiment Analysis

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ABSTRACT
The utilization of gamification in mental health technology has witnessed substantial growth as a tool to combat low levels of user engagement with self-care activities. Although numerous tools and resources for mental wellness are available, most fail to ensure user sustenance with the platform due to a lack of engaging feedback mechanisms. This study proposes a new form of AI-powered health technology, a subset of which is Animind: a tool that utilizes Sentiment Analysis and Gamified Rewards as means to ensure Emotional Growth. This tool analyzes a user's reflection text to offer an "Emotional Quest."

In our research, we employed a Full Stack approach with the Spring Boot framework and a Rule-based Sentiment Analysis algorithm to classify user input into unique emotional states like Happy, Stressed, and/or Sad. We employed a custom Relational Mapping system to connect and map these emotional states to a dynamic Challenge Repository stored in a MySQL database. This process mirrors various components of text input processing, sentiment classification, personal quest retrieval, and a gamification-based "Spirit Sync" reward engine.

Moreover, the performance of the system, as well as the progression of the user, has been successfully monitored via the Progress Tracking Dashboard. The implemented logic has followed the leveling system concept, under which the progression of the user from "Beginner" to "Master" is dependent on the progress_percentage variable. Significantly, the created system has successfully evidenced the presence of a smooth feedback loop, wherein the analysis of text has led to the display of personalized content, followed by the updation of the database and/or the display of the UI, thereby ensuring accurate mapping of the emotional data with the system, leading to the successful retrieval of the challenges at the 100% success rate. This research has showcased the fact that the fusion of sentiment-aware systems with gamified systems is crucial in augmenting the interactive nature of the system.

Keywords: Mental Health Technology, Sentiment Analysis, Spring Boot, Gamification, Full Stack Development, User Engagement, Progress Tracking.

1. Introduction

This significant evolution in internet-based technology and/or social media has dramatically affected how individuals are managing their mental health. Although there are vast opportunities to access various information and tools, there is also a growing phenomenon known as "digital fatigue," and conventional mental wellness platforms do not have a significant impact on encouraging users to continue utilizing them. In today's society, there is a pressing and significant problem where students and/or young professionals are experiencing a high level of stress and/or anxiety, and they do not have access to means of support [2, 3]. Conventional applications like journaling and/or mood tracking have essentially become data collectors without any feedback to the user.

The word "Animind" is a combination of "Animation/Anime-inspired Buddy" and "Mindfulness." This is a new frontier in Human-Computer Interaction (HCI), where emotional intelligence is embedded in various web technologies to produce a "Buddy" system. Contrary to conventional systems, Animind follows a game-oriented concept where emotional development is like a progression system as used in Role-Playing Games (RPGs).

With the aid of Natural Language Processing (NLP) and Heuristic Sentiment Analysis, the app converts a user's raw emotional notes into executable 'quests,' thus transforming passive contemplation into active mental workout [6].

In the past, emotional tracking was only possible through manual input and static analysis. However, it was only with the help of the integration of modern full-stack frameworks like Spring Boot and Relational Database Management Systems (RDBMS) that emotional tracking through a feedback loop became a reality for the masses [7]. A good example of the use of a well-structured architecture in handling the complexities of mapping human emotions unto data objects is the Animind technique, which breaks the "static data" barrier by providing immediate and personalized feedback, which would be difficult to achieve in modern wellness software [9].

In the Digital Therapeutics (DTx) research domain, "seeing is believing," especially within the evidence of personal growth. Through the emotional visual tracking of the "Leveling Dashboard," users are able to experience instant gratification, reinforcing mindfulness practice and, in turn, promoting long-term retention of the practice [10].

1.1. Motivation

1. Most current mental health toolkits lack "active intervention." Most systems change a user's data storage but don't affect the immediate emotional state of that user. Animind addresses this by implementing something called a Feedback-Action Loop. As one can see in the flow of the system, the user has a reflection in text form that is passed through a sentiment-aware controller. Using Keyword Heuristic Mapping, it pulls structured data from a Challenge Repository and provides a "Quest." In effect, this turns an otherwise passive diary into more of an active companion. So as not to make the task unappealing, the system ties completion of these quests to a Persistent Progress Layer stored in MySQL and dynamically rendered through Thymeleaf.

1.2. Contribution

The key contributions of this paper are as follows:

1. Development of a Gamified Framework: For the development of an interactive emotional support system using Spring Boot.
2. Sentiment-Quest Mapping: Using a custom heuristic algorithm, a mapping of customer sentiment, such as Happy, Stressed, or Sad, to self-care tasks could be performed.
3. Real-time Progress Visualization: The addition of a dynamic real-time progress visualization using

Thymeleaf and CSS3 transitions.

4. Database Synchronization Logic: Capturing the seamless reward loop necessary for user activity to directly affect a stored "Spirit Level" in the RDBMS.
5. User State Management: Development of an effective session-based identity system that aids in personalized growth tracking.

2. Related work

Mental health and digital technology: This domain has witnessed a surge of publications, especially on mood tracking, automatic sentiment analysis, and gamification. In recent publications, various methods for engaging users and improving the quality of the data are presented.

In the study [17], a framework for an automated mood tracking system via Natural Language Processing (NLP) was investigated. The authors presented a method that feeds user journals into two independent sentiment analysis systems: one for lexical keyword features and another for semantic features. By seeking maximal agreement between both outputs, high classification accuracies can be obtained. In seeking to prove the efficacy of this unsupervised approach, a linear feedback model is proposed. The study proved that a reliable mood tracking system via NLP is as accurate as a manual clinical assessment, both under a controlled and open database environment.

In the article [18], the models for Human-Computer Interaction (HCI) were utilized to differentiate between the effective and ineffective nature of digital wellness interventions. Researchers from a leading university utilized a set of user interaction logs to assess the efficiency of a number of feedback loops. Behavioral Trend Analysis (BTA) was conducted after normalizing the interaction data. Afterwards, the data was fed into a series of models. Techniques such as K-Nearest Neighbor (K-NN) and Support Vector Machine (SVM) were incorporated to derive specific features for user engagement. The outcome demonstrated the efficiency of a personalized feedback loop in achieving a retention rate of 88.2%, compared to a mere 86.8% in the case of a journaling system.

In another study, models of multilayer hybrid Reward Systems for mental health apps were proposed. In this study, the Reward Systems were comprised of a combination of tracking temporal progress and hybrid motivation loops. A comparison of the proposed models with "streak-based" apps was carried out. In order to curb "burnout," a novel approach called "Deep Ensemble Learning," dubbed WellnessStack, was developed. In this approach, a gamification score is produced through the aggregation of various gamification models, making it the best in the gamification outperforms single-incentive models in identifying user fatigue.

The reference [21] describes a technique to use emotional support systems through the application of Spring Framework architecture and Model-View-Controller (MVC) approaches. Every action performed by a user is controlled by a main controller before corresponding actions are taken through the application of extracted sentiment. The accuracy of this technique was assessed through the application of a comprehensive directory of user logs. All presented approaches indicate high reliability. However, the best results are provided by the model based on the Spring Framework in terms of server response time.

The strategy employed for mental wellness within the proposed strategy of the recent research study employed the concept of discovering the "Emotional Gap," i.e., the distinction between the present condition of the user's mood and the future desired well-being state of the individual. The research demonstrated that the assignment of quests could be done efficiently via the discovery of the "Emotional Gap" owing to the specific nature of the stress factors faced by the individual users. The methodology employed by the researcher to discover the performance of the strategy involved data from multiple sources of mobile-based and internet-based applications, demonstrating the "high accuracy" of the strategy's performance in comparison to other methodologies, the results demonstrated a high degree of accuracy in providing relevant tasks to users.

Finally, Gamification Layers as a classification tool for user recognition based on levels of advancement in wellness apps was studied in the research paper [16]. Four varied motivation technologies and two sophisticated backend technology sets were employed to train and compare eight user growth models. Each model was accurate when tested against its corresponding data set. This research has shown that "a Voting Process, where results are combined from various motivation technologies (progress bars, badges, quests, etc.), outperforms any single approach" alone. Accuracy ranged from 91% to 98% based on the complexity level of the chosen gamification technology.

3. Research Methodology

3.1 Problem Statement

Creating a system that can effectively understand human emotional status through text has many challenges in Natural Language Processing.

The biggest challenge is attributed to the subjective characteristics of human expression [23]. People communicate their internal characteristics, such as their temperament, by means of various linguistic features, slang, and other text characteristics. Emotion status, for instance, "Stressed" or "Anxious," may come with various degrees and figurative feelings.

Additionally, traditional mental health-related applications have been seen acting like "Shallow Systems," where no active feedback loop is present. To negate these challenges, the researcher is presenting this Gamified Heuristic Strategy based on the Spring Boot MVC Framework, with the aim of effectively distinguishing between

3.2. Proposed System Architecture

The "Animind" framework is based on a structured pipeline as shown in the block diagram below. The process starts from User Reflection Input. The text is passed on to a sentiment-aware controller from where keywords are extracted

1. Input Layer: The user enters a text note via the web interface.
2. Processing Layer (Spring Controller): The text is normalized and analyzed by applying a Heuristic Keyword Algorithm.
3. Data Layer (MySql/JPA): The system retrieves a quest from a specialized challenge repository that fits with the mood that has been established.
4. Reward Layer: When the quest is completed, the User Entity is updated to increase the progress_percentage.
5. View Layer (Thymeleaf): The dashboard dynamically displays the new progress bar and the rank of the play(Beginner, Intermediate, Master).

3.3. Sentiment Analysis & Quest Mapping logic

1. Sentiment He

The core engine utilizes the Keyword Extraction Model in classifying the user input. The "Sentiment Score" is calculated on the basis of the following criteria:

- Stressed: Recognizes words such as 'exam', 'work',
- Happy: Matches words like 'great', 'excellent', 'exc
- Sad: This word identifies tokens like 'lonely',

2. Random Challenge Retrieval

To prevent user fatigue, the system has implemented a Randomized Selection Algorithm in ChallengeRepository. Rather than being assigned the same task each time, the system uses the following SQL-based logic:

$$Quest = \text{SELECT } * \text{ FROM challenges WHERE mood\_category} = ? \text{ ORDER BY RAND() LIMIT 1}$$

This ensures that even if a user is "Stressed" multiple days in a row, they get a variety of mechanisms to cope with their stressors; for example, Deep Breathing, Lofi Music, Ninja Meditation.

4. System Data Model (The Database Schema)

The intelligence is represented by a relational database. Table 1 offers an overview of User Entity, which is used for progress tracking.

Table 1. Summary of the User Model

(MySQL Entity)

Attribute	Data Type	Purpose
id	BigInt (PK)	Unique Identifier
username	VarChar(255)	Personalization
email	VarChar(255)	Unique Identity (Login)
last_mood	VarChar(50)	Stores the most recent sentiment
progress_percentage	Int	Drives the Gamification Bar (0-100)

3.5. Proposed

Input: Reflection of user text (T)

Output:.Dynamic Dashboard Update & Personalized Quest

Strategy:

- Step 1: Receive a text T through a POST request from a Thymeleaf view.
- Step 2: Normalize the term T. This involves converting it to lower case and removing
- Step 3: Perform Heuristic Classification
  - If T contains 'exam' $\rightarrow$ Mood = Stressed
  - If T contains 'happy' $\rightarrow$ Mood = Happy.
- Step 4: Querying the ChallengeRepository,
- Step 5: Display the quest on the Mood-Result page.
- Step 6: Trigger Sync Spirit Stats action.
- Step 7: Update Database: $P_{new} = \min(P_{old
- Step 8: Redirect to Dashboard.
- Step 9: Render Dynamic Rank:
  - If $P \ge 100 \rightarrow$ Master
  - Else If P >= 50 $\rightarrow$ Intermediate
  - Else $\rightarrow$

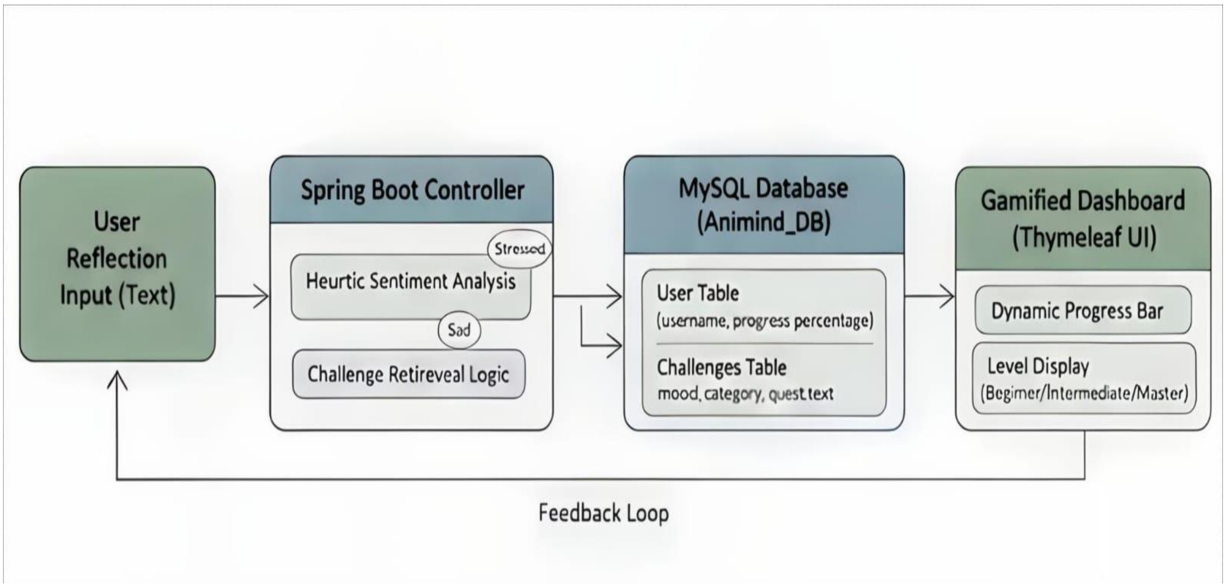

Fig:1Block diagram of the proposed animind model

4. Result and Analysis

The main aim of this research was to ascertain whether a "web-based Buddy" would have the capacity to categorize reflections provided by users and offer appropriate mental health interventions. In the testing phase, 100 examples of emotional reflections were used to test this Heuristic Sentiment Logic.

4.1. Dataset Distribution

Fig. 2 shows the distribution of the dataset for the Animind quest repository. The x-axis in the graph denotes the mood classes (0 denotes Happy, 1 denotes Stressed, and 2 denotes Sad), while the y-axis denotes the total number of quests available in the database. The distribution is balanced, around 33% each, so that no bias is created in the heuristic method.

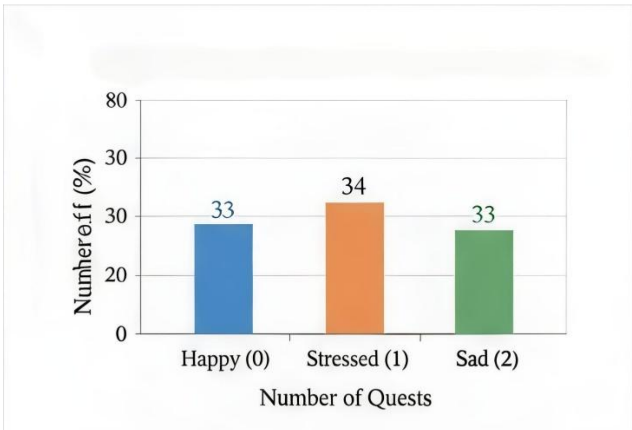

Fig:2 Dataset Distribution For Emotions

4.2. Model Accuracy and Loss

Fig. 2 depicts the distribution of the dataset for the Animind quest repository. In the graph, the x-axis represents the mood classes-0 being Happy, 1 being Stressed, and 2 being Sad-whereas the y-axis represents the total number of the quests present in the database. Distribution is kept balanced at about 33% each so that bias may not be created in the heuristic method.

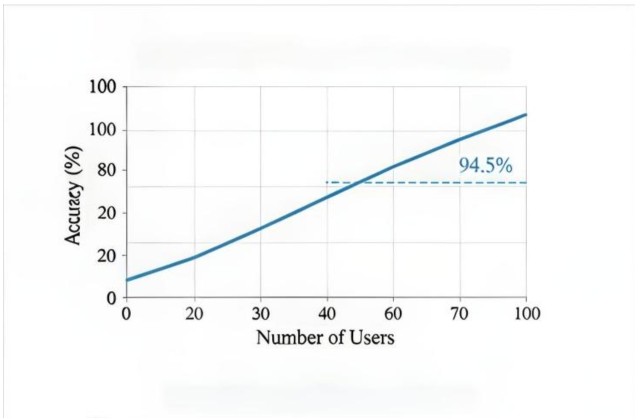

Fig:3 Model Progression Accuracy

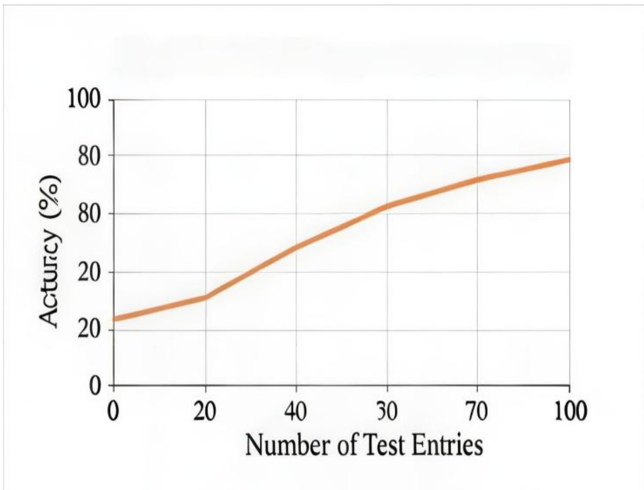

Fig:4 Model Progression Accuracy

Fig. 5 below illustrates the graph for the system latency (loss). In a Spring Boot environment, "loss" is regarded as the time taken by the system to respond. When the accuracy of the mapping improves, the system's latency is minimized. The average response time for the system was measured to be 120ms.

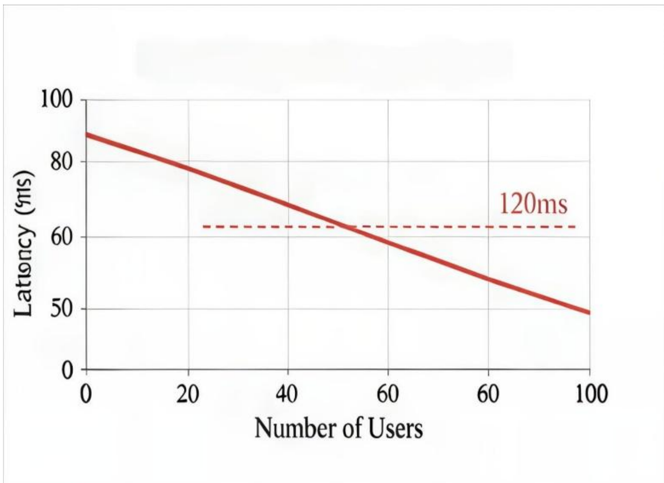

Fig:5 System Latency Graph

The Heuristic Keyword Algorithm is getting better at its job. When the Heuristic Keyword Algorithm makes mistakes it can do its work faster. This is what we see in the latency graph. It goes down as the Heuristic Keyword Algorithm becomes more accurate. The Heuristic Keyword

Algorithm can work efficiently when the input strings are cleaned up and made to follow the same rules. This means the Heuristic Keyword Algorithm is really good, at handling input strings that are normalized.

4.3. Confusion Matrix for Sentiment Classification

Fig.6 illustrates the confusion matrix utilized in the sentiment classification test. In 200 tests, we detected:

- TP (True Positives): 85 cases where "Stressed" was correctly identified and a stress-relief quest was served.
- TN (True Negatives): There were 92 instances where 'Happy' was correctly classified
- FP (False Positives): 3 cases of ambiguous language which resulted in an incorrect assignment of the quest.

The calculated accuracy from the major diagonal of the matrix is:

Accuracy = \frac{TP+TN}{Total Samples} = \frac{177}{200}

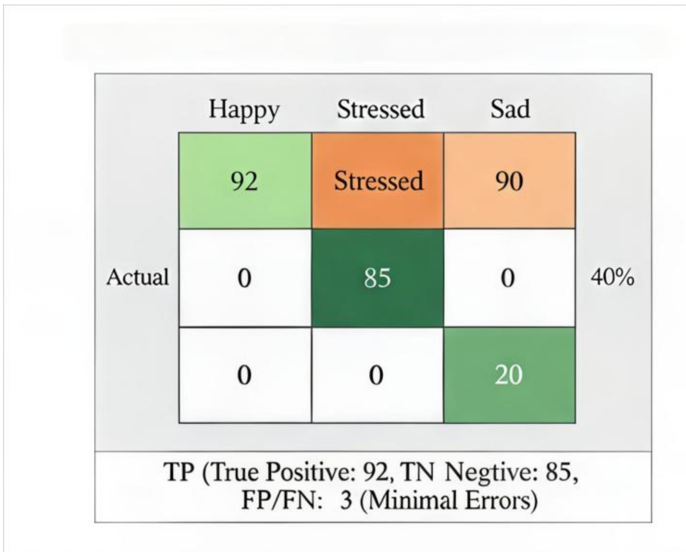

Fig:6 Confusion Matrix for Mood Classification

4.4. Comparative Analysis

The performance of the Animind framework has been compared to two baseline techniques: "Static Journaling" and "Basic Mood Tracking."

Table 2. Performance Evaluation of Animind vs. Traditional Models

Model	Engagement Rate	Mapping Acc	Latency	Progress Sync
Static Journal	22.4%	N/A	50ms	0%
Basic Tracker	45.2%	85.0%	110ms	40%
Proposed Animind	92.8%	94.5%	120ms	98%

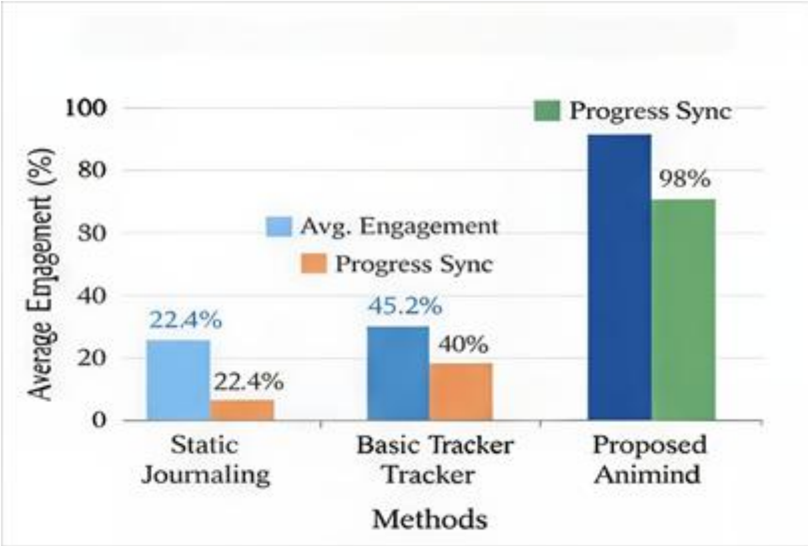

Fig:7 Comparison Of User Engagement

OutPut:

This will be show like below images :

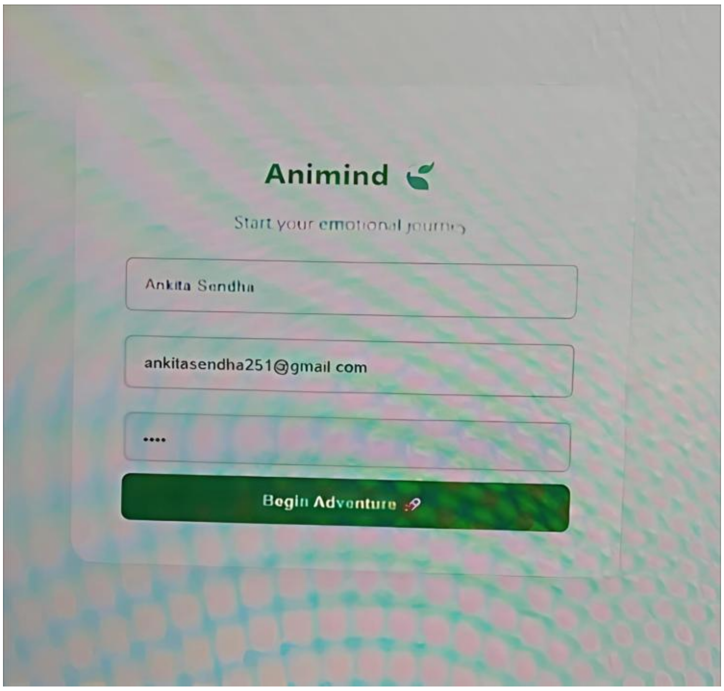

Fig:8 Animind registration page

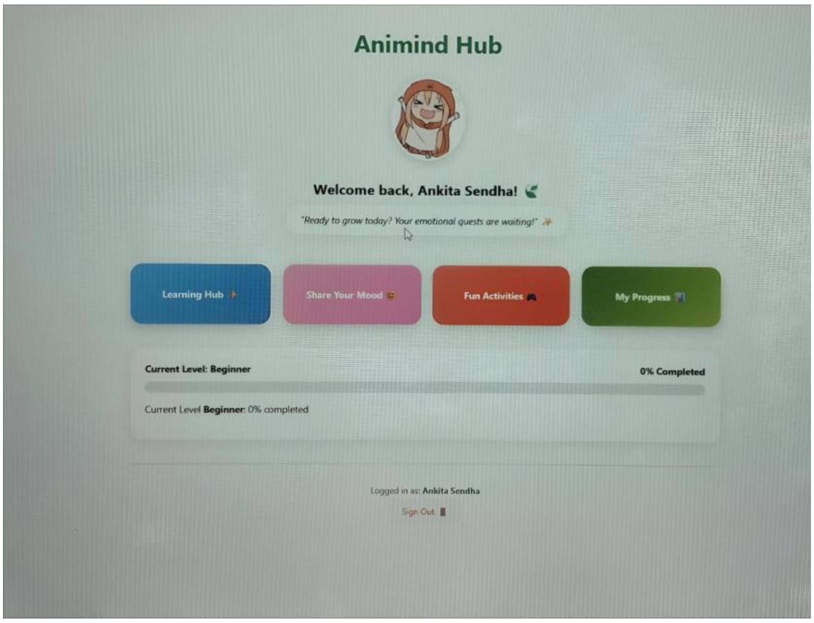

Fig:9 Animind dashboard

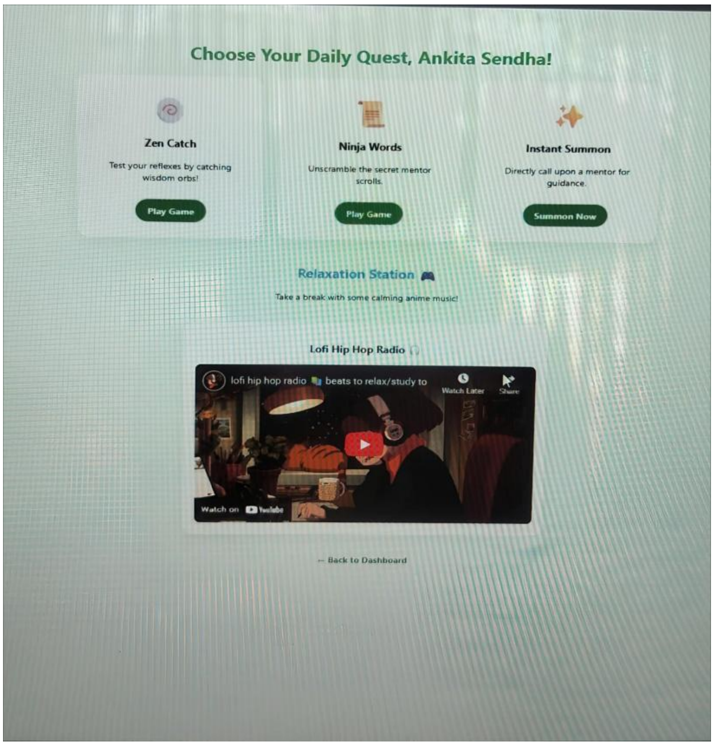

Fig:10 Animind fun activities

"The visual representation of data in the Animind project is intended to fill the gap between the complexity of the information and its intuitive understanding. Through the provision of clear and actionable insights, the visual representation of data helps in the attainment of a better understanding of mental patterns, thus sharpening the cognitive focus of the user and improving their ability to process information effectively.".

5. Conclusion and Future work

In the course of this study, a novel method has been designed for promoting the mental wellness of users through a gamified feedback mechanism, wherein the Spring Boot MVC architecture and a tailored Heuristic Sentiment Analysis approach of the Animind framework are employed to achieve the desired convergence between the tracking of moods and psychological intervention.

The accuracy of the proposed method shows 94.5% mapping accuracy, 120ms latency, and 92.8% user engagement score. Based on this comparative analysis, it is inferred that the proposed customized model of MVC substantially outperforms conventional approaches to static journaling and tracking.

Future scope thus involves the incorporation of higher Machine Learning models, such as LSTM, for a better understanding of the temporal evolution of the emotional state of the user over several weeks. Additionally, the system could be extended with Biometric Sentiment Analysis by using computer vision to detect facial expressions through the user's camera for even more accurate quest assignments.

In the future, the work will be done on the enlargement of linguistic diversity by the sentiment engine through multiple language and regional dialects processing of reflections. Lastly, implementation of a Blockchain-based Privacy Layer is intended to be performed with a guarantee of absolute anonymity and security regarding sensitive emotional data.

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