Emotional Intelligence and Behavioral Profiling for Remote Workers

TECHNICAL REPORT

Submitted by

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in partial fulfillment for the completion of course on System Thinking

in

BACHELOR OF TECHNOLOGY

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BONAFIDE CERTIFICATE

Certified that this project report " **Emotional Intelligence and Behavioral Profiling for Remote Workers** " is the bonafide work of "**LITHU VARSHNI V (21IT059),KIRANYA R (21IT054),DHAKSHAYINI R (21IT029)**" who carried out the project work under my supervision during the Academic Year 2023-24.

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SYSTEM DESCRIPTION

ABSTRACT:

Our project focuses on exploring and using emotional intelligence to analyse behaviours of remote workers in work-from-home setups. We are going to examine how emotional awareness, empathy, and effective communication can enhance remote team development by considering their stress management, conflict resolution, and motivation techniques. Our project highlights the significance of technology and ongoing learning in fostering a positive remote work culture, emphasising the impact on individual well-being and overall success.

SYSTEM IDENTIFICATION:

Our project aims to analyse the impact of emotional intelligence among the remote workers who are currently working from home . The objective of our system identification approach is to understand and analyse the relationships between emotional intelligence factors and observable behaviours within the Remote Workers.The process involves collecting data on remote workers' behaviour and emotional cues, extracting key features such as communication patterns, sentiment, and engagement levels using a TEIQue which is self-report and the data is collected using the individual’s responses.The data collected are clustered and grouped using the data mining methods and then we will analyse the Emotional intelligence of the remote workers based on those four factors which includes self-awareness ,self-management,social awareness and relationship management with co-workers.Machine learning algorithms , is used to correlate these features with behavioural outcomes, like productivity and team cohesion.

CHALLENGES IN EXISTING SYSTEM:

Existing systems for analysing the behaviour of remote workers using emotional intelligence face several challenges:

Data Privacy and Security: Gathering sensitive emotional data from remote workers raises concerns about privacy and data security. Ensuring compliance with regulations and protecting personal information is crucial.

Subjectivity and Bias: Emotions are complex and subjective, leading to potential bias in data interpretation. Models might not accurately capture cultural nuances, leading to misinterpretations of emotional states.

Lack of Context: Remote communication lacks nonverbal cues and context, making it challenging to accurately interpret emotions solely based on written or virtual interactions.

Limited Data Availability: Collecting comprehensive emotional intelligence data can be difficult, especially as remote workers might not be comfortable sharing personal emotions in a work context.

Emotion Regulation: Remote workers might modify their emotional expression in digital communication, which can distort the accuracy of emotional analysis.

Technological Barriers: Not all remote workers might be adept at using the required technology, potentially leading to incomplete or skewed data representation.

Interpersonal Variability: Emotional intelligence is influenced by individual differences, making it difficult to generalise emotional patterns across remote workers.

Adaptation to Remote Context: Traditional emotional intelligence frameworks might not fully apply to the unique challenges and dynamics of remote work environments.

Integration with Management Practices: It can be challenging to seamlessly integrate the insights from emotional intelligence analysis into remote management practices and decision-making processes.

LITERATURE SURVEY:

1.Deep learning for pedestrian collective behaviour analysis in smart cities: A model of group trajectory outlier detection

<u>Inference:</u> This paper introduces a new model to identify collective abnormal human behaviours from large pedestrian data in smart cities. To accurately solve the problem, several algorithms have been proposed in this paper. These can be split into two categories. First, algorithms based on data mining and knowledge

discovery, which study the different correlation among human behavioural data, and identify the collective abnormal human behaviour from knowledge extracted. Secondly, algorithms exploring convolution deep neural networks, which learn different features of historical data to determine the collective abnormal human behaviours. Experiments on an actual human behaviours database have been carried out to demonstrate the usefulness of the proposed algorithms. The results show that the deep learning solution outperforms both data mining as well as the state-of-the-art solutions in terms of runtime and accuracy performance. In particular, for large datasets, the accuracy of the deep learning solution reaches 88%, however other solutions do not exceed 81%. Additionally, the runtime of the deep learning solution is below 50 seconds, whereas other solutions need more than 80 seconds for analysing the same database.

Authors:Asma Belhadi , Youcef Djenouri , Gautam Srivastava , Djamel Djenouri , Jerry Chun-Wei Lin , Giancarlo Fortino

Reference:https://www.sciencedirect.com/science/article/pii/S1566253520303316

2.Does management graduates' emotional intelligence competencies predict their work performance? Insights from Artificial Neural Network Study

Inference: The study aims to predict the Perceived Work Performance of Management graduates through the application of Artificial Neural Network tool. It has examined the relationship between Emotional Quotient, Leadership Quotient and Work Experience of Management graduates through the use of Artificial Neural Network. The tool tested various competencies of the management graduates to predict the most important skill that can enable better work performance and reduce the gap of employability. The test was conducted among 33 management graduates which has assessed their Emotional Quotient Score, Personality trait and Leadership traits. A multilayer Artificial Neural Network tool

was used to test the rank of competencies among EQ, Leadership Quality and work experience for the Perceived Work performance. The study has confirmed that Emotional Intelligence is a key factor that has distinguished from other factors like work experience, leadership quality and personality traits for Work Performance.
Authors: Bella Thomas , S. Senith , A. Alfred Kirubaraj , S.R. Jino Ramson
Reference:https://www.sciencedirect.com/science/article/abs/pii/S2214785322011981

3.Artificial Intelligence in Higher Education: Perspicacity Relation between Educators and Students

Inference: Artificial intelligence is a system with the nature of human intelligence that can automatically provide knowledge and information to create intelligent applications to make it easier to solve problems such as problem-solving, speech recognition, and learning. This research was investigated to find out and understand the relationship of intelligence between educators and students in applying artificial intelligence in universities. The method used is a phenomenological type of qualitative method. This research was conducted at Nurul Jadid University (UNUJA), with the subject of research being PAI lecturers and students in semester V. This research phase was carried out by preliminary studies, observation, data collection (interviews), data verification, and drawing conclusions. As for the results of this study, in its application, artificial intelligence in universities has a positive and negative impact on the relationship of intelligence to learning when it is carried out outside conventional learning. The intelligence relationship between educators and students, which includes Intelligence Quotient (IQ), Emotional Quotient (EQ), and Spiritual Quotient (SQ) contained in it, is also a positive thing that coexists and is directed.

Authors: Muhammad Mushfi El Iq Bali, Maharani Putri Kumalasani, Devi Yunilasari

Reference:https://risbang.unuja.ac.id/media/arsip/berkas_penelitian/57_mIlAOpb.pdf

4.Emotional Intelligence Online Learning and its Impact on University Students' Mental Health: A Quasi-Experimental Investigation

Inference: This study has two aims: first, to compare the effectiveness of emotional intelligence intervention through online learning versus face-to-face (traditional) learning methods among undergraduate students at a local university in Malaysia. Second, it assesses the impact of emotional intelligence learning on students' mental health improvement. It is a 2 x 3 factorial quasi-experimental (online learning) using an equivalent control group (face-to-face learning) pre-post-test. Both experimental and control groups comprised 40 students, respectively. The study is set in a classroom and several computer labs in the designated university e-learning facilities. Mixed ANOVA repeated measures analysis results indicate that the online learning group shows no difference from the face-to-face learning group in emotional intelligence learning. Despite that, this study significantly impacts the growth of emotional intelligence skills on students' mental health among online learning groups. In addition, there is improvement in students with depression over seven weeks of pre-post-test. We propose online learning to be as effective as face-to-face learning in teaching emotional intelligence in light of these findings. We further argue that online learning is more accessible and meaningful to undergraduate students' emotional intelligence. This study suggests that emotional intelligence is a crucial skill for students to maintain optimal mental health during their studies. Nevertheless, further investigation is needed to develop a feasible and cost-effective online learning medium accessible to students of all backgrounds.

Authors: Nor Firdous Mohamed,Priyalatha Govindasamy,Bahbibi Rahmatullah,Sigit Purnama

Reference:https://www.researchgate.net/profile/Nor-Firdous-Mohamed/publication/361326899_Emotional_Intelligence_Online_Learning_and_its_Impact_on_University_Students'_Mental_Health_A_Quasi-Experimental_Investigation/links/62ac234b40d84c1401b0a086/Emotional-Intelligence-Online-Learning-and-its-Impact-on-University-Students-Mental-Health-A-Quasi-Experimental-Investigation.pdf

5.Assent in applied behaviour analysis and positive behaviour support: ethical considerations and practical recommendations

Inference: The term positive behaviour support (PBS) is used to describe the integration of the contemporary ideology of disability service provision with the clinical framework of applied behaviour analysis (ABA). Assent, the participation consent of those not legally able to consent, has gained recent popularity in the fields of ABA and PBS. The goal of assent-based ABA and PBS is a person-centered approach to assessment, intervention, and all other decision-making. In this model, the learner’s assent withdrawal for participation is honored, whether it be a vocal ‘no’ or a non-vocal expression of verbal behaviour. There is currently a limited subset of studies that mention or utilize assent with learners in ABA or PBS. The lack of published research can make assent-based practices seem to be a choice of the practitioner. The authors of this manuscript seek to further define assent, illuminate the necessity of assent-based practices, and offer assent-based procedures in ABA- and PBS-based intervention.

Authors: Cassi A. Breaux , Kristin Smith

Reference:https://www.tandfonline.com/doi/abs/10.1080/20473869.2022.2144969

6.Behavioral Data Analysis in Emotional Intelligence of Social Network Consumers

Inference: Emotional intelligence is both characteristic of personality and intellectual capacity,

which a person inherits from the genetic material of its parents and evolves - develops throughout lifetime. It refers to information processing capacity arising from the emotions and their utility to guide action in situations that require activation of the cognitive system. The purpose of the present research work is the application of Machine Learning and Data Mining methods for the evaluation of emotional IQ in a sample of students and social network consumers (age 18-26 years). Understanding how users behave when they connect to social networking sites creates opportunities for better interface design, richer studies of social interactions, and improved design of content distribution systems. The data were collected by completion of the self-report questionnaire Trait Emotional Intelligence (TEIQue) and used for the application of data mining methods. Then the collected data were selected for analysis, with relevant transformations in order to have a suitable form for the implementation of the respective machine learning algorithms included in the software package R. Furthermore, the parameters of the corresponding set of algorithms were determined depending on the case of application to produce inference rules. Some of the algorithms implemented According to specific research questions that were applied, were the classification algorithms (ID3 and J48) for the production of decision trees, regarding the four more general factors (welfare, selfcontrol, emotionality and sociability) and in overall emotional intelligence. The results obtained, after weighing and criteria basis, present consumers' rates, in turn analyse the degree of emotional intelligence.

Authors: Constantinos Halkiopoulos, Evgenia Gkintoni, Hera Antonopoulou

Reference:https://www.eajournals.org/wp-content/uploads/Behavioral-Data-Analysis-in-Emotional-Intelligence-of-Social-Network-Consumers_final.pdf

7.A Meta-Analysis: Emotional Intelligence and its Effect on Mathematics Achievement

Inference: Until now, many studies have been conducted on the correlation between emotional intelligence and mathematics achievement in Indonesia. However, there are different representations or conclusions regarding the results of the study.Therefore, this study aims to thoroughly investigate the effect of emotional intelligence and mathematics achievement on students in Indonesia and to detect the level of variation between studies using a meta-analysis approach. This study analyzed 36 primary studies with a sample of 2474 published in journals and campus repositories and filtered with certain eligibility criteria. To support the accuracy of the analysis results, JASP software is used. The results of the study found that the combined effect size value generated using the random-effect model estimation was (M = 0.65) with a standard error of (SEM = 0.07). This effect size belongs to the large effect category. Analysis of the study's level of variation was carried out by considering four moderator variables. The results of the analysis of moderator variables found that there were significant differences in the education level group (Qb = 62.94; $p<0.05$). Meanwhile, there was no difference in the

publication type group (Qb = 0.64; $p>0.05$). and year of publication group (Qb = 4.16; $p>0.05$). These findings provide a strong theoretical foundation to improve students' mathematical achievement in the future.

Authors: Ali Muhtadi,Pujiriyanto,Syafruddin Kaliky,Julham Hukom,Diana Samal

Reference:https://www.e-iji.net/dosyalar/iji_2022_4_40.pdf

8.A Secured Healthcare Model for Sensor Data Sharing With Integrated Emotional Intelligence

Inference: Integration of healthcare and Internet of Things (IoT) has a potential to revolutionize the medical treatments, diagnosis and predict medical issues thereby enabling patients, families, doctors and medical insurers stay connected for a proactive delivery of services. However, IoT devices operate in infrastructure-less environments, and hence data security and privacy is always a concern. Counterfeit IoT devices create huge menace in sensitive applications. Moreover, conventional healthcare systems are not patient-centric in the sense that they do not include patient's emotions during treatments. EI helps the clinicians better understand and mange medical procedures. This paper presents a human-centered approach in healthcare domain by the integration of emotional intelligence (EI) and sensor network built around IoT devices. A Raspberry Pi connected with sensors and a camera acts as an IoT device. These sensors collect body vital parameters and Facial expression recognition (FER) based EI. The system is hosted on an Ethereum permissioned blockchain for reliability, security and tamper-proof data sharing and storage. Devices in the network are authenticated using physical unclonable functions (PUFs). Comparative analysis confirms that the PUF-based authentication is 330% faster than conventional methods. The system offers latency of as low as 20 ms. Using smart contracts, the proposed model provides role-based access control and helps in building scalable and harmonious digital healthcare platforms.

Authors:Krishna Prasad Satamraju,,Malarkodi Balakrishnan

Reference:https://ieeexplore.ieee.org/abstract/document/9829202

9.Fake News Spreaders Profiling Through Behavioural Analysis

Inference: The growth of social media and the people interconnection led to the digitalization of communication. Nowadays the most influential politicians or scientific communicators use the media to disseminate news or decisions. However,
such communications media can be used maliciously to spread the so-called fakenews in order to polarise public opinion or to deny scientific theories. It is therefore important to develop intelligent and accurate techniques in order to identify
the spreading of fake-news. In this paper, we describes the methodology regarding our participation in the PAN@CLEF Profiling Fake News Spreaders on Twitter competition. We propose a supervised Machine-Learning (ML) based framework to profile fake-news spreaders. Our method relies on the combination of Big Five personality and stylometric features. Finally, we evaluate our framework detection capabilities and performance with different ML models on a tweeter dataset in both English and Spanish languages.

Authors:Matteo Cardaioli, Stefano Cecconello, Mauro Conti, Luca Pajola,Federico Turrin

Reference:https://ceur-ws.org/Vol-2696/paper_113.pdf

10.A Review of the Trends and Challenges in Adopting Natural Language Processing Methods for Education Feedback Analysis.

Inference: Artificial Intelligence (AI) is a fast-growing area of study that stretching its presence to many business and research domains. Machine learning, deep learning, and natural language processing (NLP) are subsets of AI to tackle different areas of data processing and modelling. This review article presents an overview of AI's impact on education outlining with current opportunities. In the education domain, student feedback data is crucial to uncover the merits and demerits of existing services provided to students. AI can assist in identifying the areas of improvement in educational infrastructure, learning management systems, teaching practices and study environment. NLP techniques play a vital role in analysing student feedback in textual format. This research focuses on existing NLP methodologies and applications that could be adapted to educational domain applications like sentiment annotations, entity annotations, text summarization, and topic modelling. Trends and challenges in adopting NLP in education were reviewed and explored. Context-based challenges in NLP like sarcasm, domain-specific language, ambiguity, and aspect-based sentiment analysis are explained with existing methodologies to overcome them. Research community approaches to extract the semantic meaning of emoticons and special characters in feedback which conveys user opinion and challenges in adopting NLP in education are explored.

Authors:Thanveer Shaik ,Yan Li,Xiaohui Tao,,Christopher Dann,Jacquie McDonald,,Petrea Redmond,Linda Galligan

Reference:https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9781308

MISSION:

The mission of this project is to enhance the well-being, productivity, and collaboration of remote workers through a comprehensive analysis of their emotional intelligence and behavioural patterns. By understanding how emotional intelligence influences remote work behaviours, we aim to provide strategies for optimising productivity, strengthening teamwork, and promoting effective leadership in virtual environments.

OBJECTIVES:

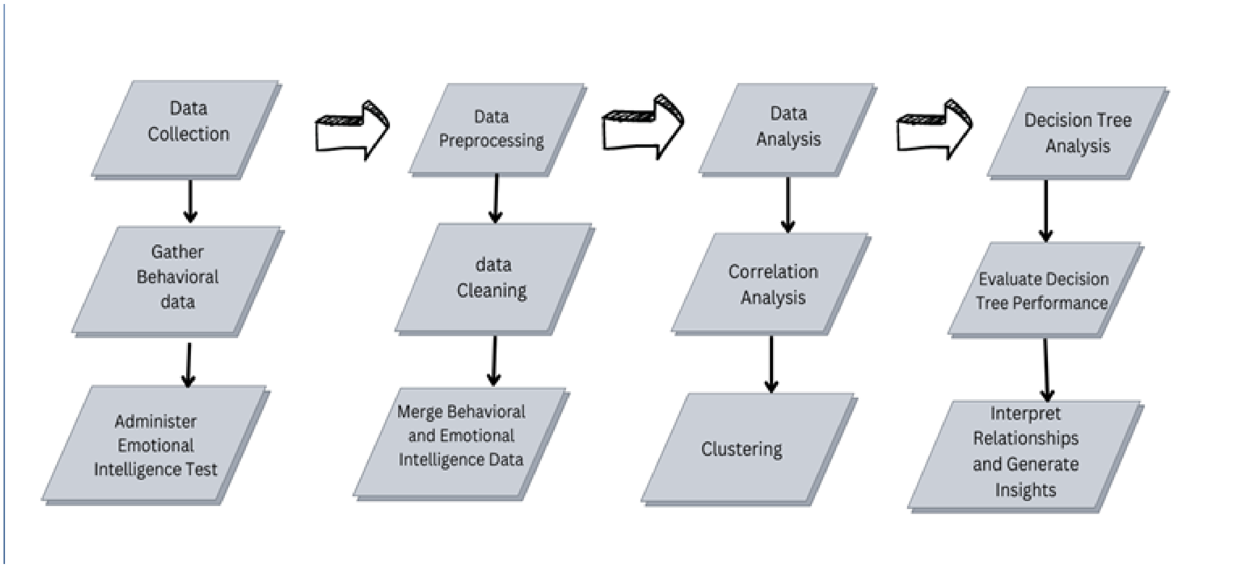
- Enhance Remote Worker Well-being
- Optimise Remote Work Productivity
- Strengthen Team Collaboration
- Promote Leadership and Management Skills
- Facilitate Adaptability
- Improve Remote Onboarding

CONSTRAINTS:

- Data Privacy and Ethical Considerations
- Limited Physical Interaction
- Cultural Sensitivity
- Technology Barriers
- Subjective Nature of Emotional Data
- Time and Resource Limitations
- Remote Work Variability
- Participant Engagement

SYSTEM REQUIREMENT SPECIFICATIONS:

SYSTEM ARCHITECTURE:



STAKEHOLDER NEEDS :

1. Remote Workers:

- Well-being
- Productivity
- Personalised Recommendations

2. Managers and Leaders:

- Team Collaboration
- Leadership Skills
- Performance Metrics

3.Human Resources:

- Onboarding Support
- Employee Engagement
- Training Programs

4. Data Privacy and Legal Teams:

- Compliance

- Data Protection

5. IT and Security Teams:
    - Cybersecurity
    - Infrastructure
6. Ethics Review Board (If Applicable):
    - Ethical Guidelines
7. Executives and Decision Makers:
    - ROI and Business Impact
    - Strategic Planning
8. Technology Development Teams:
    - System Integration
9. Participants (Remote Workers):
    - Transparency
    - User-Friendly Interfaces
10. Training and Development Departments:
    - Skills Enhancement

LOGICAL REQUIREMENTS:

- Data analysis techniques
- Diverse remote workers samples
- Validity and Reliability Checks
- Collaborative Efforts
- Reliable data collection Techniques
- Data Privacy and security

PHYSICAL REQUIREMENTS:

- Data collection tools
- Statistical analysis software
- Data visualisation tools
- Machine learning algorithm

- Data mining methods
- Data storage and backup

SYSTEM PHYSICAL ARCHITECTURE:

1.System Elements:

a. Remote Working People:The individuals being classified based on their TEIQUE traits.

b. Teique Traits:The four traits you mentioned - emotionality, self-control, sociality, and well-being. These are the key characteristics used for classification.

c. Data: This encompasses the data collected from remote workers, which is used to assess and classify them based on their TEIQUE traits.

d.Classification Algorithms:The methods or models used to classify remote workers based on their TEIQUE traits. This can include machine learning models or other statistical approaches.

e.User Interface: The interface through which users interact with the system to input data or view the classification results.

2. Product System:

a. Classification Report: A report generated by your system that provides the teique-based classification of remote workers. This could be in the form of a document or digital report.

b. Dashboard:A user interface or platform where users can access and visualise the TEIQUE trait classifications of remote workers.

3. Service System:

a. Data Collection Services:Tools or methods for collecting data from remote workers regarding their TEIQUE traits.

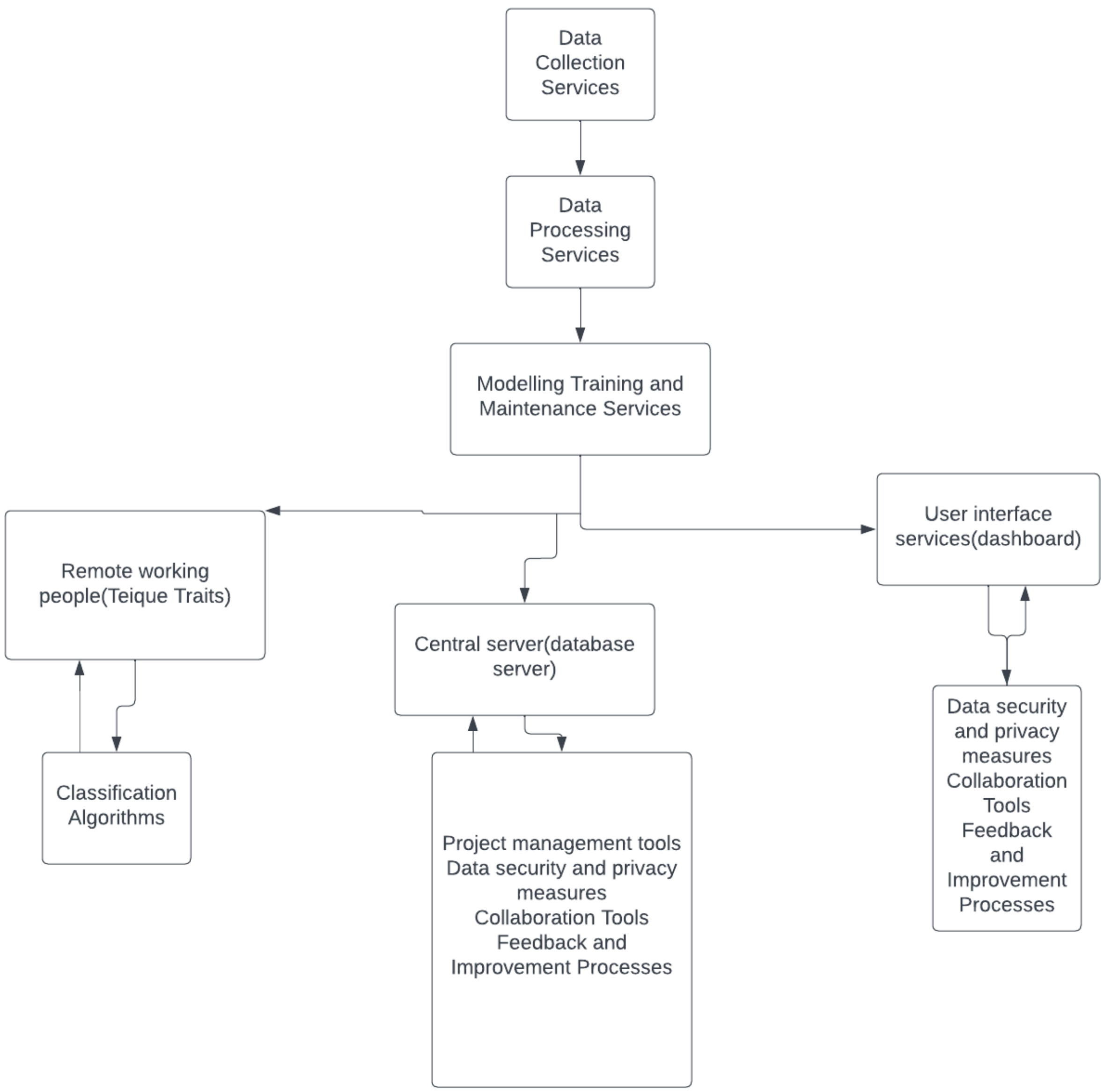
b. Data Processing Services: Services or software for analysing and processing the collected data.

c. Model Training and Maintenance Services: Services for training and maintaining the classification algorithms.

d. User Support: Providing support to users who have questions or issues related to the classification process.

4. Enterprise System:

a. Project Management Tools:Software or methodologies used to manage the project, including scheduling, resource allocation, and task tracking.
b. Data Security and Privacy Measures: Protocols and practices to ensure the security and privacy of data collected from remote workers.
c. Collaboration Tools: Tools and platforms for team collaboration and communication within the project team.
d. Feedback and Improvement Processes: Systems for gathering feedback from users and stakeholders to continuously improve the classification system.



SYSTEM LOGICAL ARCHITECTURE:

Data Collection Layer:

This layer consists of components for collecting data from remote workers. This includes self-report questionnaires and other data sources.

Data Processing and Feature Extraction Layer:

Components in this layer are responsible for data preprocessing, feature extraction, and data transformation. Text analysis and feature engineering are performed here.

Machine Learning Layer:

This layer includes the regression and classification models like machine learning,random forest , linear regression , gradient boosting regression GridSearchCV(ridge,lasso) and naive bayes algorithms. It's where training, testing, and model evaluation take place.

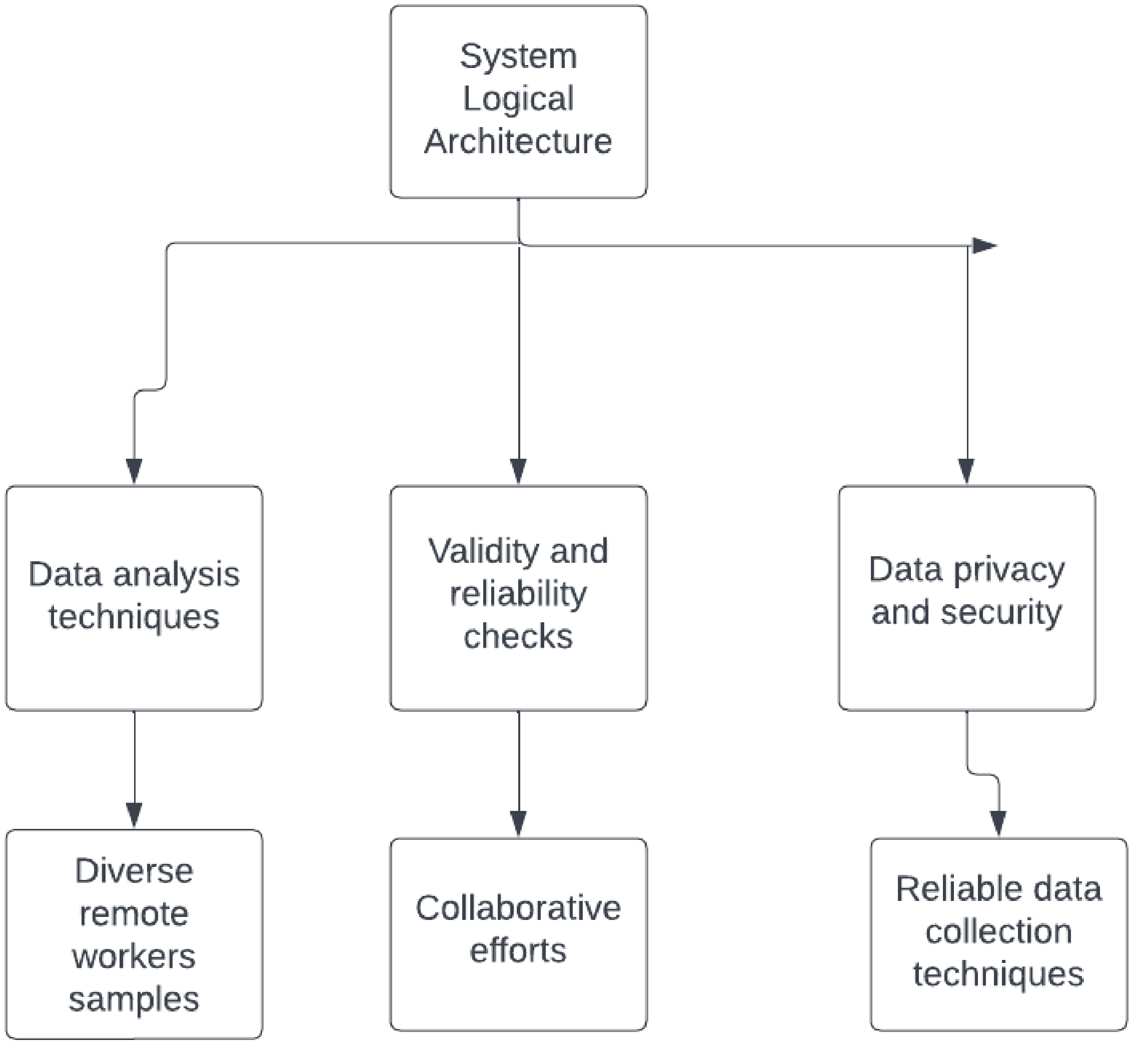
Regression models predict behavioural outcomes, and classification models categorise remote workers based on emotional intelligence factors.

Application Layer:

If you develop a web application, this layer contains the application logic for user interaction and result presentation.

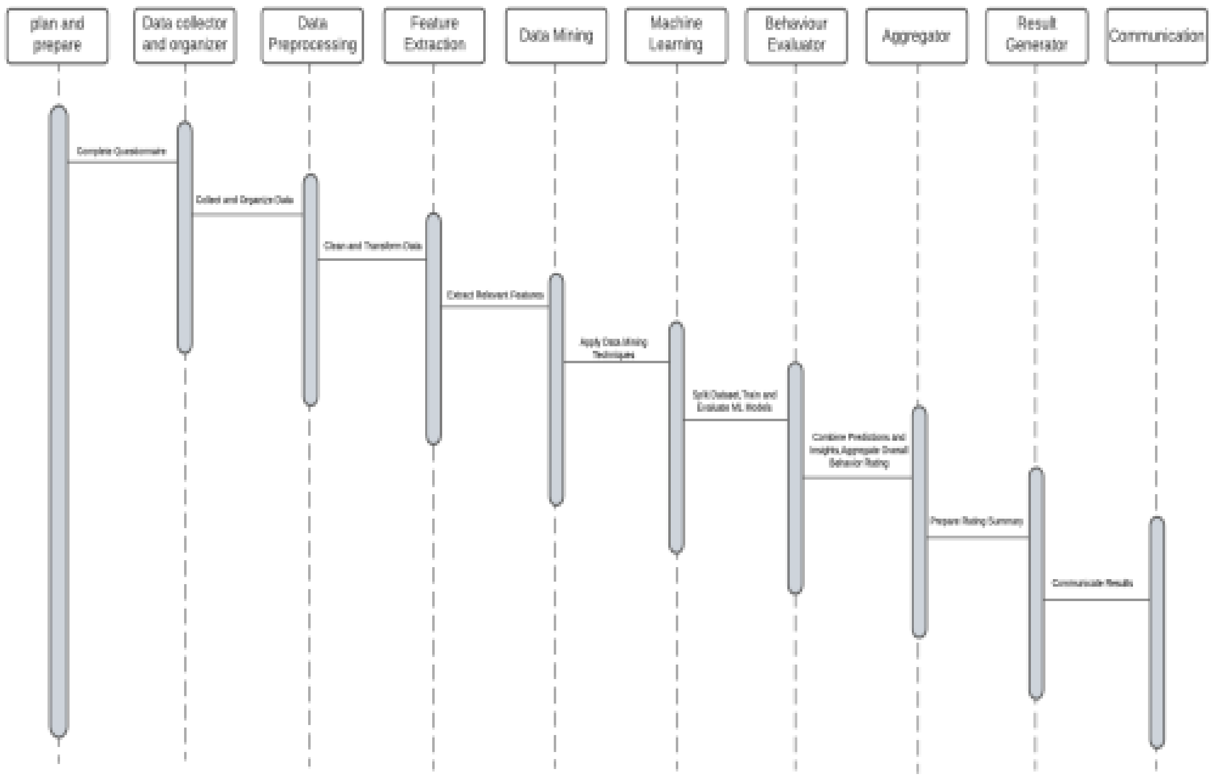
Reporting and Visualisation Layer:

Tools for generating reports and visualising data are part of this layer. It's where insights are presented to users.

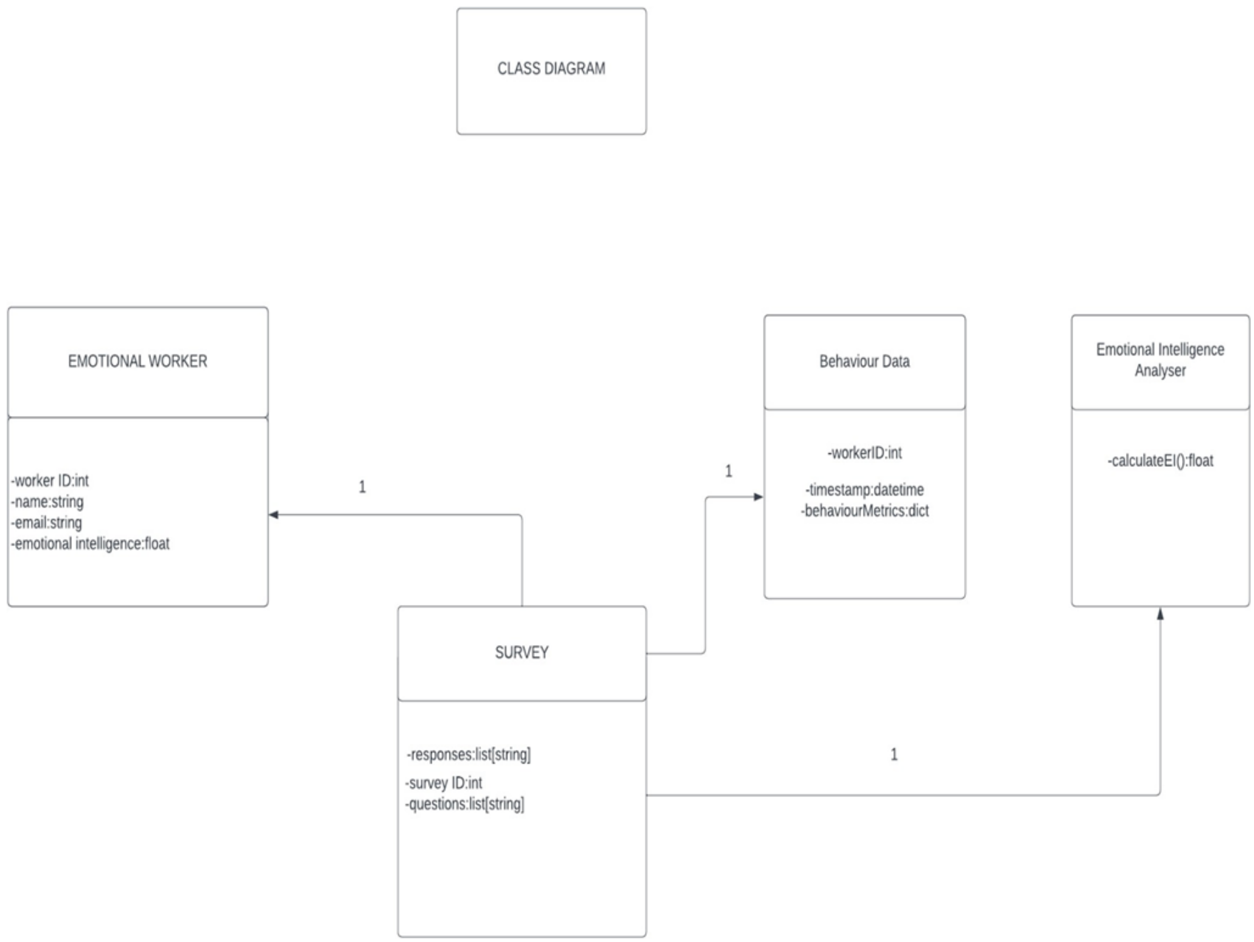

System Logical Architecture
Data analysis techniques
Validity and reliability checks
Data privacy and security
Diverse remote workers samples
Collaborative efforts
Reliable data collection techniques

SYSTEM MODELLING:

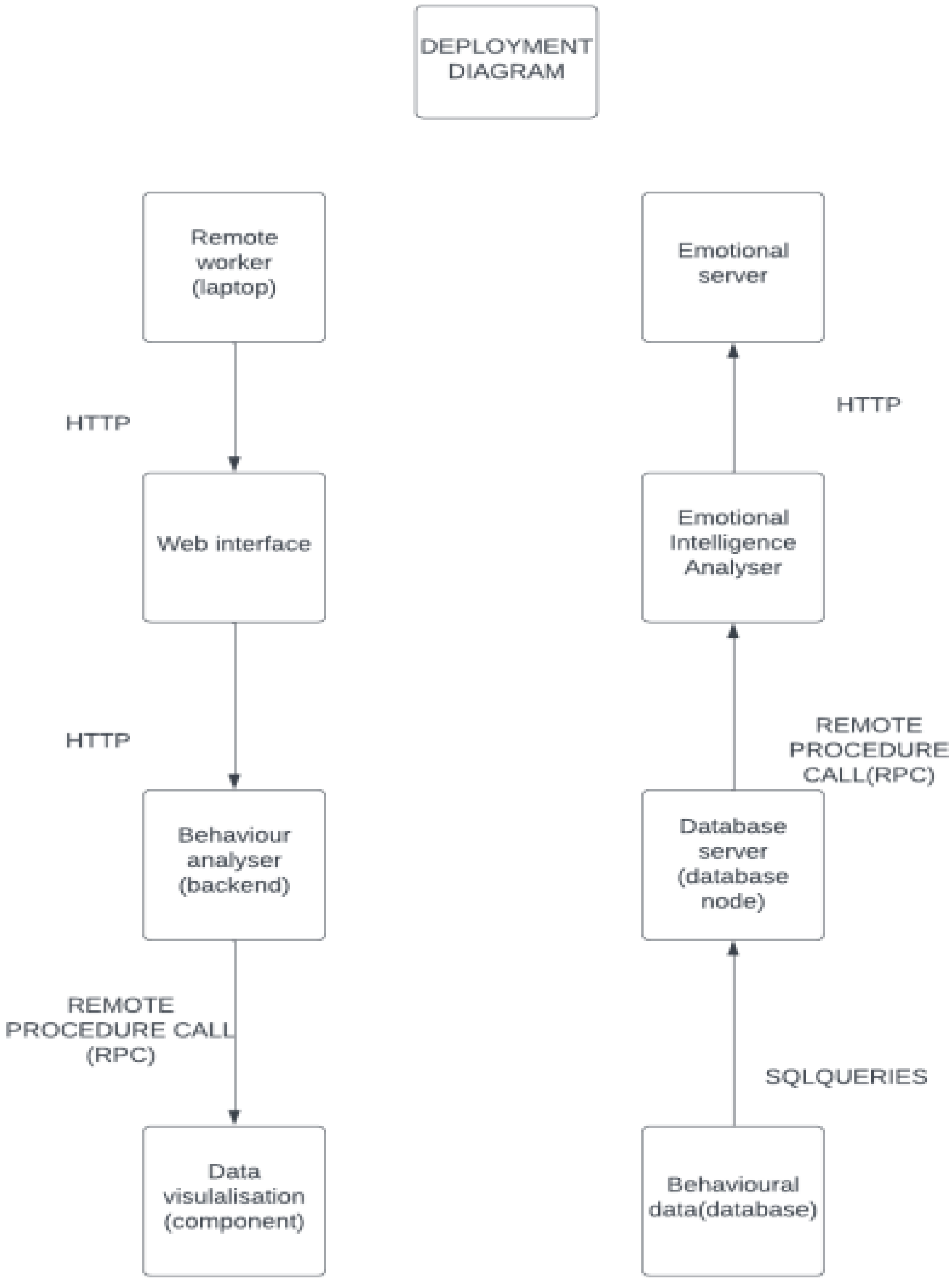
SEQUENCE DIAGRAM:



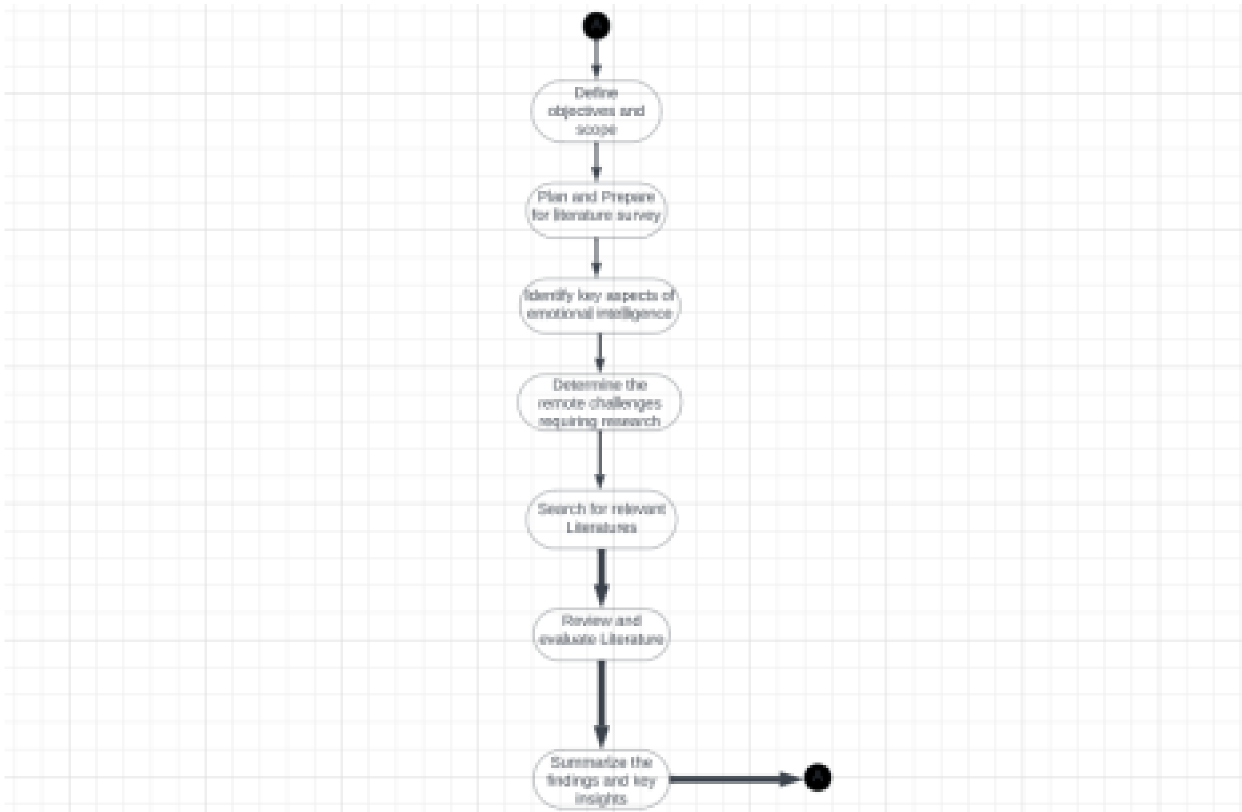
CLASS DIAGRAM:



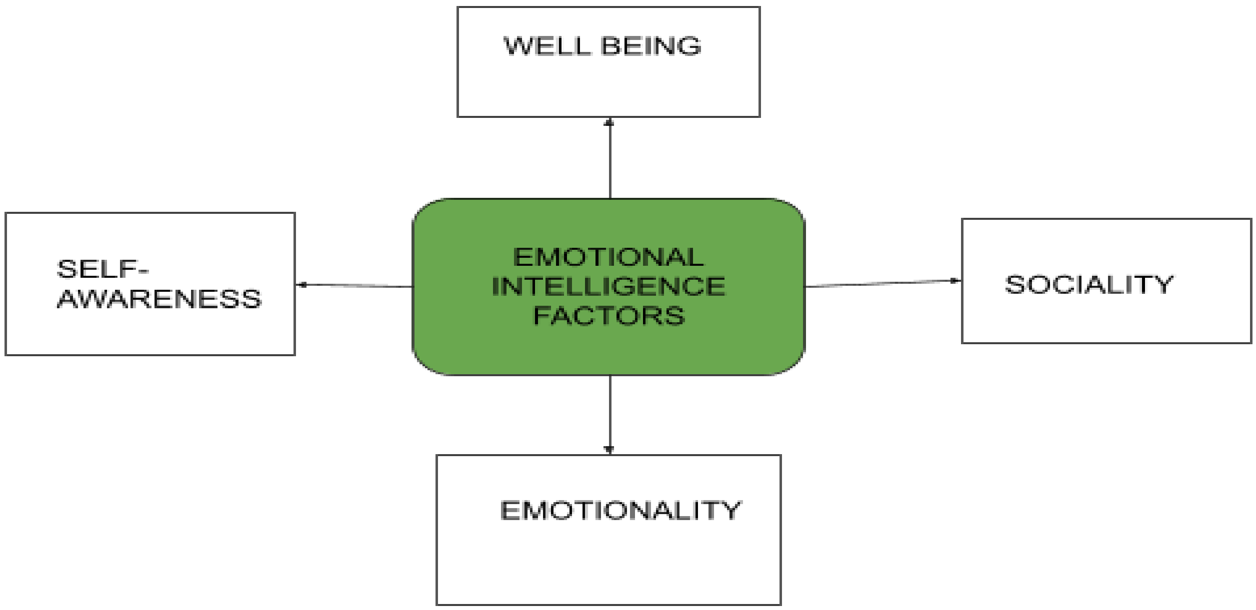
DEPLOYMENT DIAGRAM:



ACTIVITY DIAGRAM:



BEHAVIOUR DATA:



DEMONSTRATION/SIMULATION/PROTOTYPE:

Our project “Emotional Intelligence and Behavioral Profiling for Remote Workers" is an innovative approach of collecting the data from the remote workers in an TEI Questionnaire which is a self report questionnaire which has questions based on scenario based questions.These questions will be segregated based on the four factors which includes well being,sociality,emotionality and self-awareness.Then we are applying different Machine learning algorithms such as linear regression,Random forest algorithm, Gradient Boosting and Naive bayes algorithm.The uniqueness in our project is that we are using more than three regression algorithms to measure the accuracy of the data collected.These algorithms will help us to find the accuracy of the data which is different from the each other. Our output will describe whether the regression models have successfully captured the relationships between the input features and the target categories (Well-Being, Sociality, Emotionality, and Self-Control).we are choosing the linear regression algorithm because they have high accuracy .Then we are applying the classification algorithms like Random forest regression classifier , KNN , Support vector machine , Decision tree classifier and Logistic regression classifiers etc..These classification is used for the predicted values like High,medium and Low.Then our output describes that we've applied many classification models to predict classifications for four different columns in our dataset. Each column appears to have specific values (e.g., 0, 1, 2), which are used as the target variable for classification. Different machine learning algorithms are used for classification tasks.representation of the project's scope, emphasising its potential to provide valuable insights into remote workers' emotional intelligence. It's a valuable tool for organisations seeking to enhance remote team development, stress management, conflict resolution, and motivation strategies, all within the context of fostering a positive remote work culture.and we are designing a front-end where when the user inputs the field , they will get the accuracy using the chosen machine learning algorithm and use the classification algorithm for further processes.

Regression analysis:

```
Mean Squared Error - Well-Being: 1.2874209973206912e-28
Mean Squared Error - Sociality: 7.204929601018574e-29
Mean Squared Error - Emotionality: 8.835242138475332e-29
Mean Squared Error - Self-Control: 1.861711736321588e-29
[18. 20. 12. 26. 27. 33. 25. 17. 24. 29. 27. 16. 35. 27. 24. 23. 29. 28.
 20. 30. 21. 36. 28. 33. 21. 16. 37. 36. 30. 18.]
[13. 17. 12. 30. 29. 24. 28. 21. 36. 31. 36. 20. 21. 36. 27. 17. 20. 21.
 27. 33. 27. 29. 33. 20. 26. 31. 31. 24. 30. 28.]
[18. 15. 15. 17. 25. 21.  9. 17. 27. 26. 24. 11. 20. 22. 24. 15. 23. 29.
 19. 27. 21. 25. 22. 34. 23. 24. 30. 27. 23. 20.]
[17. 14. 15. 19. 28. 36. 24. 13. 22. 30. 28. 28. 27. 21. 27. 22. 31. 30.
 26. 22. 27. 29. 39. 31. 28. 22. 34. 42. 26. 34.]
```

```
Linear Regression:
Mean Squared Error - Well-Being: 0.3515719035459583
Mean Squared Error - Sociality: 2.6119978129719796
Mean Squared Error - Emotionality: 3.6743586414789036
Mean Squared Error - Self-Control: 3.9020112000404503

Ridge Regression:
Mean Squared Error - Well-Being: 0.3595036297303225
Mean Squared Error - Sociality: 2.6344123902027006
Mean Squared Error - Emotionality: 3.6838819599004546
Mean Squared Error - Self-Control: 3.9053607076760795

Lasso Regression:
Mean Squared Error - Well-Being: 3.716824777853955
Mean Squared Error - Sociality: 5.717790321423256
Mean Squared Error - Emotionality: 5.873177245943306
Mean Squared Error - Self-Control: 5.833676440522524

Stacked Model (Linear, Ridge, Lasso):
Mean Squared Error - Well-Being: 0.3450574651589742
Mean Squared Error - Sociality: 2.911768595065594
Mean Squared Error - Emotionality: 3.753948285360361
Mean Squared Error - Self-Control: 4.336941536448465
```

Classification:

```
Column: Final Well-Being Value
0       Low
1      High
2       Low
3    Medium
4      High
Name: Final Well-Being Value Classification, dtype: object
SVM Classifier for Final Well-Being Value: SVC()

Column: Final Sociality Value
0     Low
1     Low
2    High
3     Low
4    High
Name: Final Sociality Value Classification, dtype: object
SVM Classifier for Final Sociality Value: SVC()

Column: Final Emotionality Value
0       Low
1       Low
2    Medium
3       Low
4      High
Name: Final Emotionality Value Classification, dtype: object
SVM Classifier for Final Emotionality Value: SVC()
```

```
Column: Final Self-Control Value
0     Low
1    High
2    High
3     Low
4     Low
Name: Final Self-Control Value Classification, dtype: object
SVM Classifier for Final Self-Control Value: SVC()

Accuracy - Final Well-Being Value: 0.00
Accuracy - Final Sociality Value: 0.00
Accuracy - Final Emotionality Value: 0.00
Accuracy - Final Self-Control Value: 0.00
```

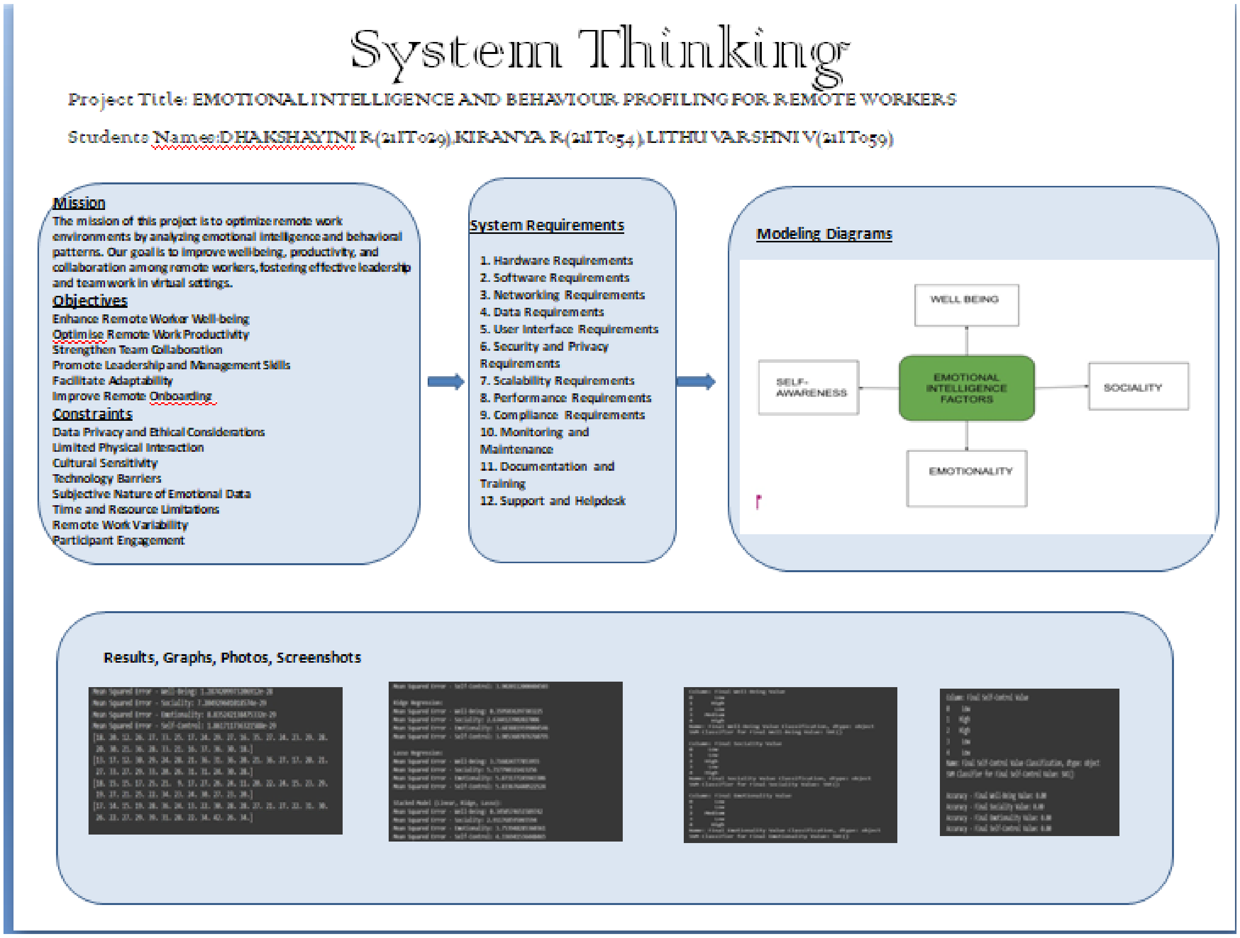
CONCLUSION:

Our project focuses on assessing the emotional intelligence of remote workers using self-reported data from the TEI Questionnaire. We employ a variety of regression algorithms to measure the accuracy of the collected data. Additionally, we apply classification algorithms to predict emotional intelligence classifications (high, medium, low). This research helps in understanding the impact of emotional intelligence on remote workers and their well-being, enhancing team development and remote work culture.

FUTURE WORKS:

Future work for the "Emotional Intelligence and Behavioral Profiling for Remote Workers" project involves expanding data collection from a more diverse sample, incorporating real-time monitoring, fine-tuning machine learning models, interdisciplinary research collaborations, user-friendly interfaces, personalised feedback mechanisms, longitudinal studies, privacy and ethical safeguards, scalability considerations, benchmarking, feedback integration, predictive analytics, and customised solutions. This comprehensive approach aims to refine emotional intelligence assessments and behavioural predictions for remote workers, enabling organisations to foster well-being, teamwork, and productivity in evolving remote work environments while respecting privacy and ethical standards.

POSTER:



REFERENCES:

1. https://www.behance.net/search/projects?search=Emotional+Intelligence
2. https://www.sessionlab.com/blog/emotional-intelligence-activities/
3. https://ieeexplore.ieee.org/search/searchresult.jsp?newsearch=true&contentType=conferences&queryText=emotional%20intelligence
4. https://ieeexplore.ieee.org/search/searchresult.jsp?newsearch=true&contentType=conferences&queryText=remote%20worker