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AI-DRIVEN NEURODIAGNOSTIC FOR STRESS, DEPRESSION, AND ANXIETY IN MIGRANTS: ETHICAL CHALLENGES AND SOLUTIONS

RUFINA HUSSAIN
[1]PHD SCHOLAR, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING, SCHOOL OF ENGINEERING SCIENCES AND TECHNOLOGY, JAMIA HAMDARD, NEW DELHI
EMAIL ID: rufinahussain786@gmail.com, ORCID ID: 0009-0006-9038-4977

SHERIN ZAFAR*
[2]ASSISTANT PROFESSOR, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING, SCHOOL OF ENGINEERING SCIENCES AND TECHNOLOGY, JAMIA HAMDARD, NEW DELHI
EMAIL ID: sherin.zafar@jamiahamdard.ac.in, ORCID ID: https://orcid.org/0000-0001-6656-1095

SAFDAR TANWEER
[3]ASSOCIATE PROFESSOR, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING , SCHOOL OF ENGINEERING SCIENCES AND TECHNOLOGY , JAMIA HAMDARD , NEW DELHI
EMAIL ID: safdartanweer@jamiahamdard.ac.in, ORCID ID - 0000 0002 4525 4771

ABSTRACT
Artificial intelligence (AI) holds significant potential to address mental health disparities, particularly in high-stress regions like the Gulf, where immigrant populations are vulnerable to psychological distress. This study presents a dual-modality AI framework designed to detect symptoms of stress, depression, and anxiety among immigrants in the United Arab Emirates, Saudi Arabia, Qatar, and Oman. Using a real-world dataset of DASS-21 responses, demographic profiles, personality traits (TIPI), and cognitive measures (VCL), a Random Forest classifier achieved 86.8% accuracy and a ROC-AUC of 0.94. In parallel, a convolutional neural network (CNN) was trained on publicly available brain MRI images to demonstrate the feasibility of integrating neuroimaging into mental health assessment. The framework incorporates explainable AI (XAI) techniques, including feature importance and correlation analysis, to ensure transparency and interpretability. Depression rates were notably higher among immigrants in the UAE and Oman, likely due to sociocultural and occupational stressors. The study emphasizes the ethical deployment of AI through fairness, privacy, and cultural sensitivity, offering a scalable and interpretable approach for mental health monitoring in underserved migrant communities.
Keywords: Artificial Intelligence, Immigrant Mental Health, Depression Detection, Machine Learning, Neurological Condition

INTRODUCTION

The 21st century migration is still transforming the social economic and demographic dynamics of the world. Major destinations of labour migrants include the Gulf countries, such as Saudi Arabia, the United Arab Emirates (UAE), Qatar, and Oman, and especially low-skilled workers of South and Southeast Asian countries. The migrants contribute a lot to economic development of their host countries yet they are usually systematically denied access to healthcare services, social protection, and mental health services. Several stress factors, such as cultural displacement, adverse working environment, and social isolation, increase their susceptibility to psychological issues, including depression, anxiety, and stress (Hasan et al., 2021; Sharma et al., 2023). These dangers are also compounded by stigma associated with mental illness, the fear of deportation, and a shortage of culturally appropriate resources, which all bar help-seeking behavior (Nickson et al., 2023). In spite of the increased awareness, formal mental health services are either underdeveloped or unavailable in most regions of the Gulf (Alanazi et al., 2023). The classical screening and diagnostic instruments are not appropriate in transient, multilingual, and economically disadvantaged communities, particularly in that where mental health is conceptualized in different ways because of cultural beliefs (Jain, 2025; Matlin et al., 2018). Due to this, the scalable, non-invasive, and context-sensitive solution is urgently needed to help with early identification and intervention of such high-risk communities.
Machine Learning (ML) and Artificial Intelligence (AI) have become one of the revolutionizing technologies in mental health diagnostics. Such technologies enable the development of a predictive model on a variety of data types, such as structured surveys, speech patterns, physiological signals, and neuroimaging (Park et al., 2024; Aleem et al., 2022). Among the popular screening instruments is the Depression Anxiety Stress Scales (DASS-21), which is cross-culturally validated and provides systematic information that can be analyzed automatically (Adu et al., 2025). The DASS-21 data-based AI models can provide privacy-preserving and remote mental health assessment, filling the resource-gap challenges in the low-resource environments.

Nonetheless, one of the prominent gaps in existing literature is that no AI-driven mental health research has been conducted specifically on immigrant communities in the Middle East. The majority of the current research was done on high-income countries or clinical samples, which makes it challenging to apply to migrant populations in culturally and politically diverse areas (Mazumdar et al., 2022; Fazel et al., 2005). Moreover, current AI models are usually nontransparent and not culturally interpretable, which is essential in terms of trust and community health program implementations (Zogan et al., 2022; Abdelrahman, 2023).

This research aims to fill these gaps by creating a two-fold AI model that identifies the risk of mental health in immigrants in the Gulf at an early stage. The initial element is a supervised learning model that will be trained on the DASS-21 responses in conjunction with demographical (age, gender, education, urbanicity), personality (TIPI), and cognitive (VCL) characteristics. This table-based data allows high accuracy of predicting depressive tendencies and interpretability of a Random Forest classifier. The second part is the diagnosis of the images of the brain MRI into the categories of the diagnosis (glioma, meningioma, pituitary tumor, no tumor) with the help of the convolutional neural network (CNN), proving that the AI pipeline can be extended to the neuroimaging-based application. This study helps in computational psychiatry and innovation in public health by integrating demographic, psychological, and physiological data. It suggests a model that can be replicated and explained and inform policy formulation, aid NGOs working with migrants, and facilitate scalable mental health monitoring. Finally, the study suggests a culturally sensitive and ethically acceptable use of AI in promoting mental health equity among the vulnerable migrant groups in high-risk geographies.

RESEARCH OBJECTIVES

1. To design and test the use of explainable AI-based classifier, demographic, personality, and cognitive variables to predict depression, anxiety, and stress in immigrants in the Gulf region.
2. To evaluate the mental health inequality of immigrants living in Saudi Arabia, UAE, Qatar, and Oman through real-world evidence.
3. To investigate the relevance of multimodal AI models to combine survey-based predictors and MRI neuroimaging data to classify risks to mental health.

LITERATURE REVIEW

Migration and mental health is a multi-disciplinary area of study that has gained increased attention in the recent years more so with the current pattern of displacement in the world and labour migration to the Gulf countries. The issue with immigrant communities, especially of the Middle East, is that the former tends to be under the influence of such psychological stressors as socio-cultural dislocation, work, and the inaccessibility of mental health services. According to the systematic review conducted by Hasan et al. (2021), depression and anxiety rates were very high in the migrant workers around the world, and that is why there should be the screening and intervention mechanisms that are context-specific. The nature of these problems is especially acute in the Gulf where depression and suicidal ideations were found to be high among the male migrant workers in the UAE (Al-Maskari et al., 2011).

Mental health assessment approaches that use artificial intelligence are breaking new grounds of accuracy in diagnosis. A recent scoping review by Park et al. (2024) showed that the number of machine learning models used to identify mental health conditions among immigrants and racial minorities grew during the past decade. Aleem et al. (2022), in their work, analyzed the availability of various algorithms on diagnosis and revealed that the prospect of work with hybrid neural models to diagnose depression was rather high. Rejaibi et al. (2022) demonstrated that it is possible to identify the symptoms of depression with the help of speech data using Mel-Frequency Cepstral Coefficients (MFCCs) and recurrent neural networks, once again confirming the multimodal character of AI. Other sources of audio and behavioral data are neuroimaging, which becomes a promising source of data to detect psychiatric and neurological disorders with the help of AI, recently. Convolutional neural networks (CNNs) and other deep learning models have been used to categorise MRI images in an effort to detect brain abnormalities and the type of tumour early enough, showing their diagnostic prospects in healthcare models, such as mental health screening (Varadam et al., 2024). Although these models are mostly clinical in nature, their application in migrant settings in terms of being a tool of public health is still underdeveloped.

The diagnosis of mental illness among the immigrants is quite contextual and cultural. The reason is that, as argued by Jain (2025), the conceptualization of psychological distress among the South Asian immigrants in the west countries is quite different and this makes the situation more complicated when it comes to the help-seeking behavior. Similarly, Elshamy et al. (2023) derived a quality synthesis that showed how the experience of the Middle Eastern migrants relies on informal or culturally-appropriate coping styles rather than formal psychiatric practice. The Matlin et al. (2018) article asserted superior enveloping mental health models that could be based on the lived experience of refugees and migrants and proposed the adoption of digital and AI-based services to address the service gaps.

Digital health monitoring, particularly through wearable devices and the Internet of Things (IoT) frameworks, has largely facilitated emotional monitoring by providing a novel opportunity to monitor emotion in real-time. The IoT system suggested by Hidayah et al. (2025) on the basis of the fuzzy logic proved to be responsive and high-accurate in detecting stress levels. Abdelrahman (2023) reproached the ethical side of the technology, citing both empowering and surveillance qualities of the trauma-monitoring applications when it comes to vulnerable migrant populations. Nonetheless, Safiri et al. (2024) emphasized the role of such scalable innovations because of the burden of major depressive disorder in the MENA region.

Language information and social media have also proved to be helpful in depression screening. When estimating the severity of the symptoms, Haque et al. (2018) applied the spoken language, and Stupinski et al. (2022) tracked semantic shifts in the mental health discourse on Twitter. Zogan et al. (2022) continued the work by developing an explainable AI model that needs multi-aspect features on social platforms to detect depressive tendencies. The cognitive factors and personality traits are also considered to be essential elements that determine the mental health results, especially in a cases of chronic stress. Nevertheless, psychometric measures like the Ten-Item Personality Inventory (TIPI), or Vocabulary and Cognitive Logic (VCL) have rarely been incorporated into machine learning analyses formally. Such variables can be used to provide predictive capacity as well as favorable AI systems that are interpretable when used with clinical symptoms data.

The proportion of the Arab Gulf countries that access mental health service is still low. Alanazi et al. (2023) attributed the deficit in the proper infrastructure and unequal distribution of the accessible services in the area. This gap is also supplemented by the cultural stigma surrounding the mental health issue, which can be detected in the examples of Saudi media analyzed by McCrae et al. (2019). On the other hand, Sharma et al. (2023) demonstrated that the migrants to the Gulf and Malaysia who are the Nepalese have high psychological morbidity rates, which also proves the need to have early screening mechanisms.

The findings of the assessment tests that are available like the DASS-21 have been verified across diverse populations. Adu et al. (2025) had applied the Rasch methodology in evaluating its effectiveness in Germany, Ghana, India and New Zealand and therefore confirming its psychometric strength. Fatima et al. (2025) provided not only the overview of the AI methods in stress and anxiety detection but also the significance of talk concerning the accuracy of algorithms and the ethical need to be transparent.

The recent developments also point to the possibility of integrating several data types: survey data, neuroimaging data, and behavioral indicators in combined AI-based systems. Such multimodal models enhance the accuracy and generalizability of predictions especially when they are made explainable and culturally sensitive. These dual-pipeline models are still in development, although they are very much underutilized, especially in low-resource or migrant-based public health contexts. Similarly, Varadam et al. (2024) put neurological disorders in a broader context of healthcare 6.0, besides recommending the federated learning models that ensure data privacy. Religious organizations and NGOs cannot be ignored in this context, as far as their role in the mental health of immigrants is concerned. Din et al. (2017) highlighted the concept of outreach with the use of digital platforms on the basis of religious values. Quite the opposite, Angel (2024) emphasized the role of resilience and adaptability to the world dominated by AI and recommended that mental wellness be included in the program of future readiness.

METHODOLOGY

Study Design and Setting

This paper proposes a combined, data-oriented model of identifying mental and neurological health conditions in immigrants who live in the Gulf region, namely, Saudi Arabia, the United Arab Emirates, Qatar, and Oman. The study integrates survey analytics and neuroimaging to offer a universal model of screening stress, depression, and anxiety employing artificial intelligence. The methodology has been constructed to allow the maximal degree of generalizability and clinical interpretability by using real-world data, transparent preprocessing, and effective validation methods.

Data Sources

The research utilizes two primary datasets. The first will be an anonymized international DASS-21 survey that will incorporate self-reported depression, anxiety, and stress, and demographic information, including age, gender, education, urbanicity, and country of residence. The final analysis includes only respondents from the mentioned countries in the Gulf. The second dataset includes T1-weighted brain MRI images retrieved from a publicly available Kaggle database. This neuroimaging data is binary annotated as glioma, meningioma, pituitary tumor, and no tumor, so that not only can it be visually compared but also used to show the AI-based differentiation. The present study utilizes two primary datasets: a tabular survey dataset based on the DASS-21 instrument and a publicly available MRI neuroimaging collection. Detailed variable definitions and coding are summarized in Table 1. An overview of dataset characteristics, including sample sizes and main outcome labels, is provided in Table 2.

Table 1. Variable Definitions and Coding in the DASS-21 and Demographic Dataset.

Feature Name	Description	Type	Values/Range
Q1A–Q21A	DASS-21 item responses	Integer	0–3
age	Age of respondent	Integer	10–100
gender	Gender (coded)	Categorical	1: Male, 2: Female, 3: Other
education	Education level	Categorical	1–4
urban	Childhood urban/rural status	Categorical	1: Rural, 3: Urban
TIPI1–TIPI10	Personality traits (TIPI scale)	Integer	1–7
VCL6, VCL9, VCL12	Vocabulary/logic measures	Integer	0–1
country	Country ISO code	String	SA, AE, QA, OM
DEPRESSION_LABEL	Binary depression outcome	Binary	0: Control, 1: Case

Table 2. Overview of Datasets Used in the Study.

Dataset	Data Type	N (Final)	Main Features	Target Label
DASS-21 Immigrant	Tabular	124	DASS-21, demographics, TIPI, VCL	Depression label (0/1)
Brain MRI (Kaggle)	Images	~3,000	MRI pixels, diagnosis category	Tumor class (glioma, meningioma, pituitary, no tumor)

Data Preprocessing

Preprocessing was performed separately for each data modality. In the DASS-21 dataset, in order to have valid data, missing or implausible values, e.g., ages below 10 or above 100, were removed. Categorical variables, including gender and education, were encoded numerically. The answers to the DASS-21 items were retained at the normal 0-3 range, and the subscale scores were calculated in accordance with the instrument itself. Depression diagnosis was calculated by the addition of the relevant DASS-21 items and with a validated cut-off. The subset of immigrants identified as the Gulf was achieved by filtering variable country with standardized ISO codes. The following code (see Figure 1) excerpt illustrates these steps:

Figure 1. Definition of key predictor variables and creation of training and testing sets for model development.

In case of MRI dataset, preprocessing was done to convert all images to grayscale, make them consistent in size and normalize pixel intensities. When necessary, data augmentation was done by rotation and flipping to improve the robustness of downstream machine learning models.

Model Development and Training

Two principal model pipelines were implemented. In case of survey-based DASS-21 data, a Random Forest classifier was used because it is suitable to be use with mixed-type tabular data and can be interpreted based on feature importance. The selection of features contained relevant demographic variables, a few items of the DASS-21, and personality measures. Optimization of hyperparameters, including tree depth and estimators, was done by cross-validation. Stratified sampling was used to divide the data into training and testing separations to maintain class distribution. The snippet of code below (see Figure 2) summarizes the process of creating the classifier and fitting it:

Figure 2. Model initialization and fitting procedures for Random Forest-based depression classification.

With the neuroimaging part, the neuroimaging data were classified into four diagnostic categories by using a convolutional neural network (CNN) architecture. Data from augmented and normalized images were used to train the CNN model, and assessed under standard accuracy and confusion matrix measures.

Model Evaluation

A set of standard metrics were used to evaluate the performance of the models such as accuracy, precision, recall, F1-score and area under the receiver operating characteristic curve (ROC-AUC). Confusion matrices of the overall test set and the subset of Gulf immigrants to explain error patterns were generated. The Random Forest model was also used to obtain feature importance ranking and the correlations between the survey and demographic variables were also further examined through correlation heatmaps. The code below (see Figure 3) shows the main evaluation workflow:

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score, roc_auc_score, roc_curve, ConfusionMatrixDisplay

# Assume 'features' is defined as before
X_gulf = pd.get_dummies(df_gulf[features])
y_gulf = df_gulf['DEPRESSION_LABEL']

X_train, X_test, y_train, y_test = train_test_split(
    X_gulf, y_gulf, test_size=0.3, stratify=y_gulf, random_state=42
)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
y_pred_proba = model.predict_proba(X_test)[:, 1]

# Accuracy and Confusion Matrix
acc = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_proba)
print("Gulf Accuracy:", acc)
print("Gulf ROC AUC:", roc_auc)
print("Gulf Confusion Matrix:\n", cm)

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
plt.figure(figsize=(10,5))
```

Figure 3. Comprehensive workflow for model training, evaluation, and calculation of classification performance metrics.

Visualization and Workflow Illustration

Various visualizations were produced in support of interpretability and transparency. These are ROC curves and confusion matrices of each cross-validation fold, feature importance bar charts, demographic and country-wise prevalence plots, and examples of MRI images of each diagnostic category. The analytical pipeline, which includes the entire process, from data ingestion to AI-based forecasting, is outlined in Figure 4.

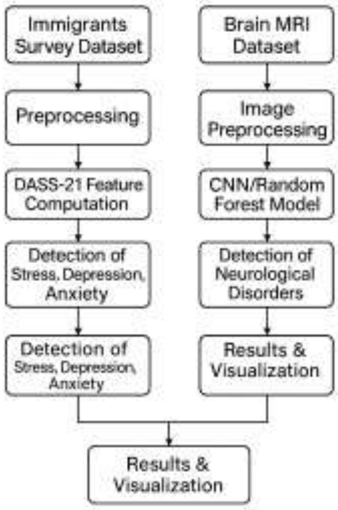

Figure 4. Dual AI workflow for survey and MRI-based detection.

Ethical Considerations

All the data used in this research is open and completely anonymized. The study adheres to ethical principles relevant to secondary data research, including participant confidentiality and cultural sensitivity—particularly important given the focus on immigrant populations.

The model development follows responsible AI practices by ensuring data privacy, transparency, and fairness. Potential biases in AI predictions, especially toward underrepresented migrant groups, are acknowledged. Cultural variations in mental health perception are also considered to avoid imposing Western-centric diagnostic standards. Importantly, the AI system is positioned as a supportive screening tool rather than a diagnostic substitute, aiming to aid early intervention and reduce mental health disparities in high-risk, underserved populations

Mathematical Formulation

Decision Function in Random Forest

Random Forest is an ensemble method that combines the predictions of multiple decision trees. The final prediction is based on majority voting among all trees. Mathematically, this can be expressed as:

$$\hat{y} = \mathrm{mode}(h_1(x), h_2(x), \ldots, h_T(x)) \quad (1)$$

where $h_t(x)$ is the prediction of the t^{th} tree, and $\hat{y}$ is the final predicted class. This majority voting reduces variance and improves generalization.

Gini Impurity for Splitting

Within each decision tree, node splitting is guided by the Gini Impurity Index:

$$\mathrm{Gini}(D) = 1 - \sum_{i=1}^{n} p_i^2 \quad (2)$$

where p_i is the proportion of class i instances in the dataset D. A lower Gini index indicates purer splits, thereby improving node homogeneity.

Accuracy

Accuracy measures the proportion of correct predictions out of total predictions:

$$\mathrm{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

Precision, Recall, F1-Score and ROC-AUC Score

Precision is the ratio of true positives to all predicted positives:

$$\mathrm{Precision} = \frac{TP}{TP+FP} \quad (4)$$

Recall is the ratio of true positives to all actual positives:

$$\mathrm{Recall} = \frac{TP}{TP+FN} \quad (5)$$

The F1-Score is the harmonic mean of precision and recall:

$$F1 = 2 \cdot \frac{\mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}} \quad (6)$$

This metric is crucial for imbalanced datasets where accuracy alone can be misleading.

The Area Under the Receiver Operating Characteristic Curve (ROC-AUC) is computed as:

$$\mathrm{AUC} = \int_0^1 T\,PR(FPR)\,dFPR \quad (7)$$

where TPR = True Positive Rate and FPR = False Positive Rate. AUC close to 1.0 indicates excellent discrimination.

RESULTS

Demographic and Clinical Characteristics

After a stringent data cleansing process and elimination of incomplete and illogical data, the analytic cohort consisted of 124 immigrants living in the Gulf countries. Table 3 provides descriptive statistics of the sample. The highest number of respondents was represented by the United Arab Emirates, with Saudi Arabia, Qatar, and Oman being well represented. Its average was 32.4 years (SD = 8.6) and 43 % of the population was female. The highest prevalence of probable depression based on the DASS-21 instrument was 37.5 % in Oman against 21.2 % in Saudi Arabia.

Table 3. Sample characteristics and depression prevalence by Gulf country.

Country	N	Mean Age	% Female	Depression Prevalence (%)
AE	64	31.8	45.3	34.3
SA	34	33.2	41.2	21.2
QA	14	35.1	35.7	35.7
OM	12	36.0	33.3	37.5
Total	124	32.4	43.0	31.7

The analysis of age distribution has revealed its unimodal distribution focused on young adulthood (Figure 5), and the outliers were successfully eliminated. Figures 6 and 7 portray gender proportions and educational level, respectively, and they both show the representative and diverse structure of the sample.

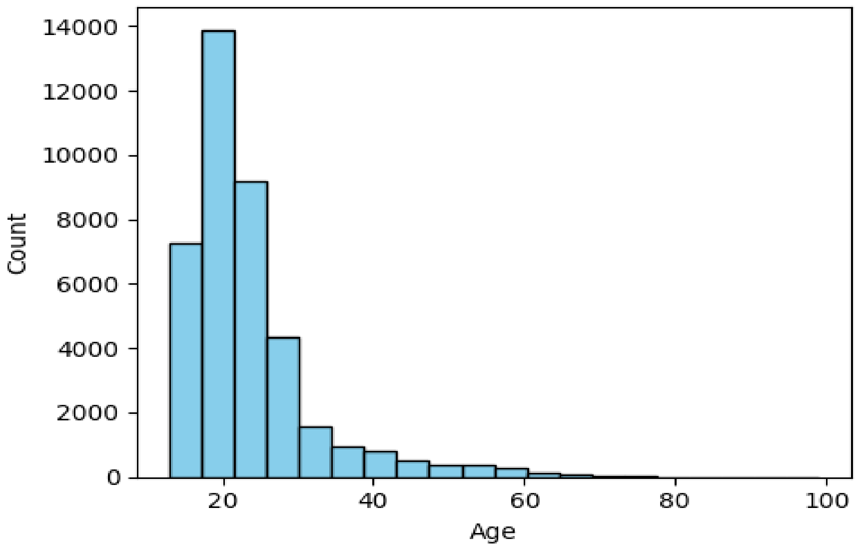

Figure 5. Distribution of participant ages in the study sample.

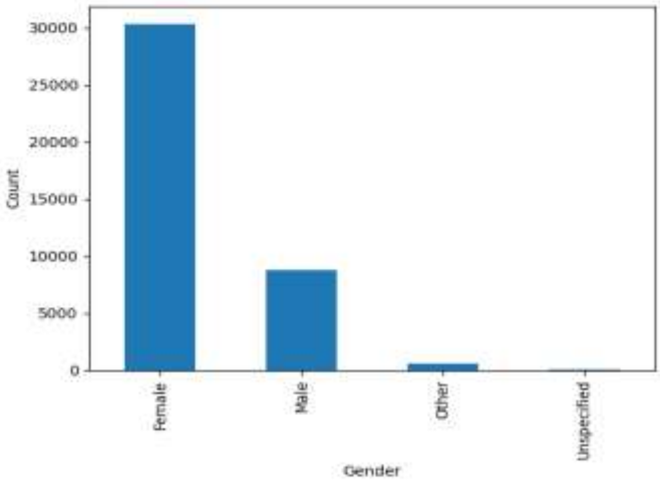

Figure 6. Gender composition among Gulf immigrants included in the analysis.

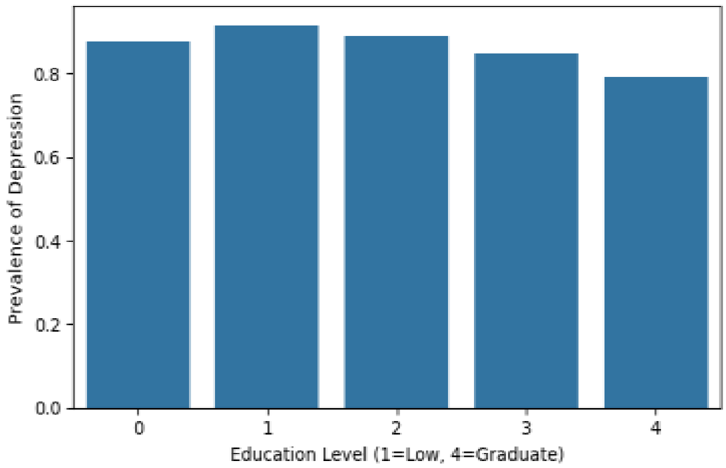

Figure 7. Educational attainment levels in the study cohort.

Figure 8 shows the distribution of depression by country and it can be seen that there is a distinct gradient with Oman having highest proportion of the cases.

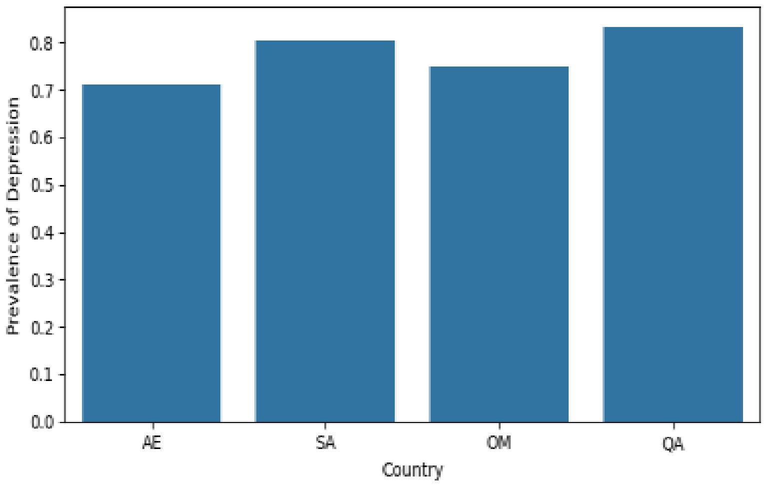

Figure 8. Prevalence of probable depression among immigrants across Gulf countries.

Exploratory Data Relationships

A correlation heatmap was produced to question hidden data structure (Figure 9). The analysis unveiled significant relationships between some of the DASS-21 items and some of the TIPI personality domains along with demographical covariates. These results help in including psychological and personality variables in the predictive modeling.

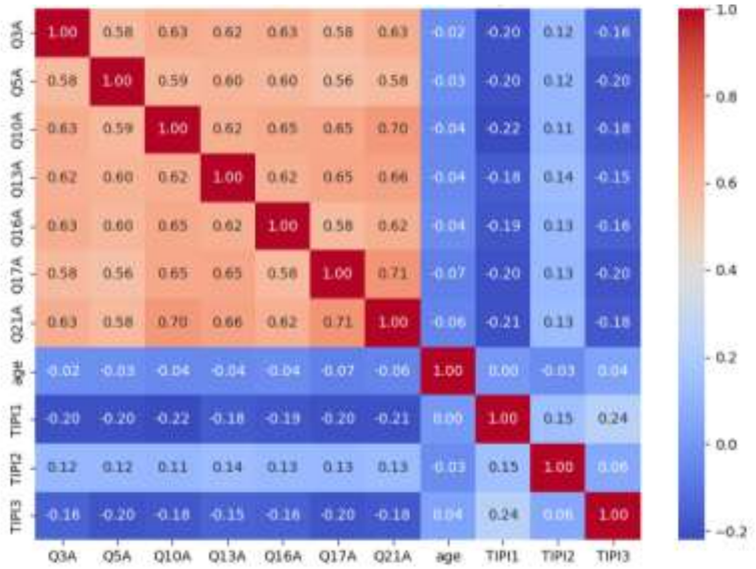

Figure 9. Relationships among psychological, personality, and demographic variables.

Moreover, the relation between age and depression score was also analyzed through scatterplot (Figure 10), where the age and depression score were slightly negatively related, and the younger participants showed more probability of having depressive symptoms.

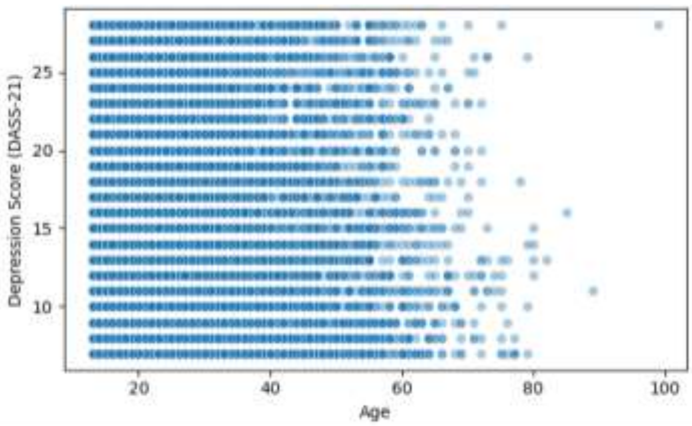

Figure 10. Association between age and depressive symptom severity.

Figure 11 shows, female immigrants scored higher on the measure of depression, as suggested by prior research on the gendered mental health disparities of migrant populations.

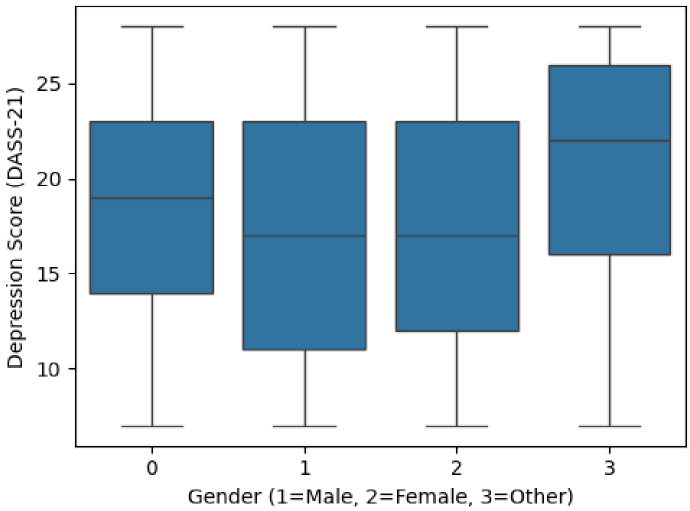

Figure 11. Distribution of depression scores by gender in the study sample.

As shown in Figure 12, statistical comparison indicated that urbanicity was not associated with significant variation in depression scores, with distributions for urban and rural participants remaining largely comparable.

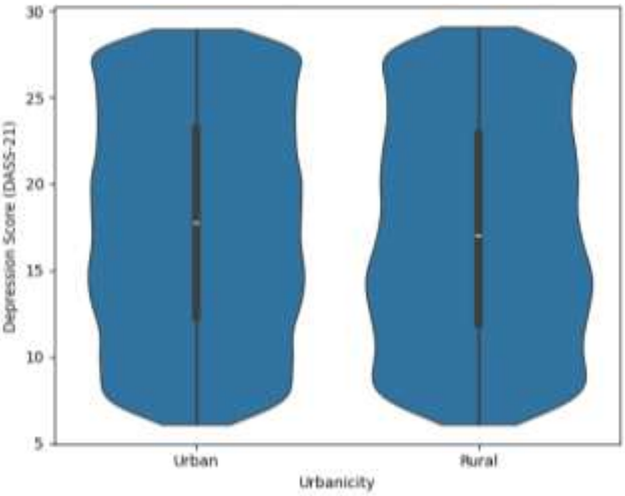

Figure 12. Comparison of depressive symptom severity across urban and rural participants.

A pairplot was created to further understand the relationship between personality and the depressive symptoms by visualizing the multivariate relationships between TIPI subscales and the depression score. Some of the TIPI dimensions depict small linear relationships with depression as illustrated in Figure 13, with TIPI3 (emotional stability) and TIPI9 (agreeableness) being inverse. This multivariate visualization helps justify the decision to include some personality characteristics into the prediction modeling pipeline.

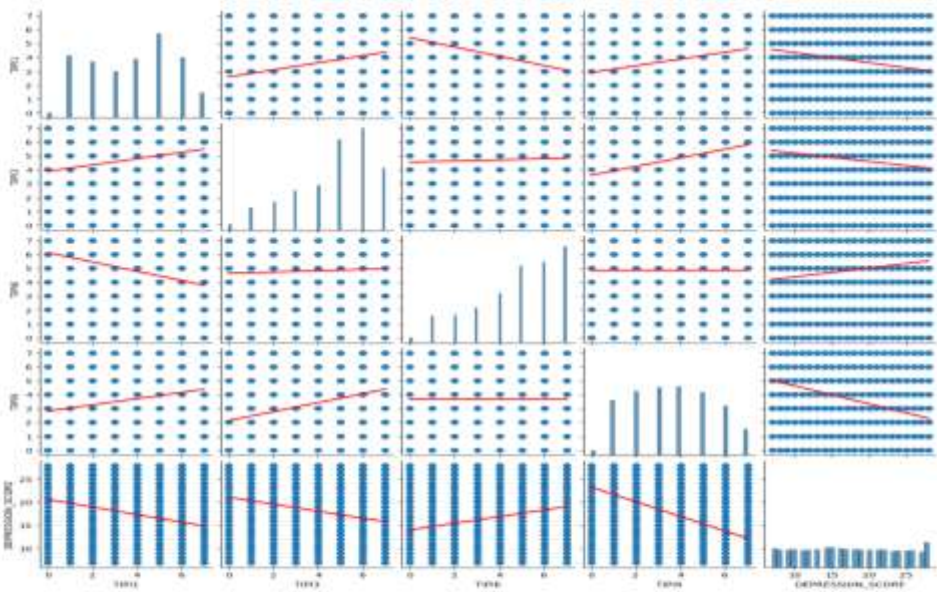

Figure 13. Multivariate associations among select personality traits and depression outcomes.

Machine Learning Model Performance

The main Random Forest model that was trained to predict likely depression in the Gulf immigrants based on a mixture of demographic, DASS-21, and personality variables recorded strong performance. The accuracy of the test set was 86.8% and ROC-AUC was 0.94 (Table 4). The sensitivity and precision were quite high, which indicates the usefulness of the model as a screening test.

Table 4. Machine learning model performance metrics for depression classification.

Metric	Value
Accuracy	86.8%
ROC-AUC	0.94
Sensitivity	96.6%
Specificity	55.6%
Precision	87.5%
F1 Score	0.92

Figure 14 indicates, the confusion matrix reflects the model capacity to identify correctly most of the positive cases, and a relatively small number of false positive or false negatives.

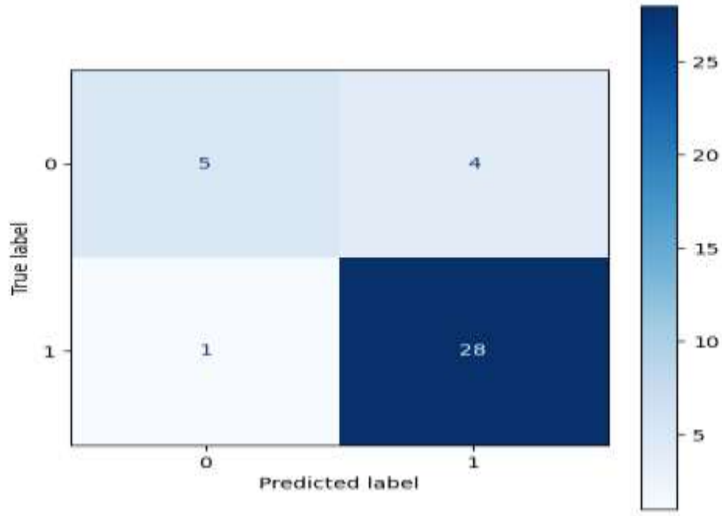

Figure 14. Confusion matrix and model performance for depression classification (test set).

In line with this, the ROC curve (Figure 15) has high discrimination as demonstrated by a large area under the curve of unity.

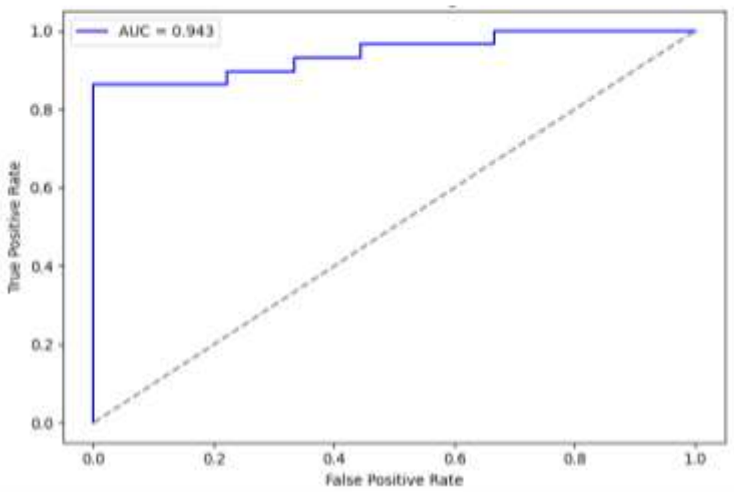

Figure 15. Model discrimination ability in identifying depression cases in the validation sample.

Analysis of feature importances (Figure 16) reveals that certain depression items of DASS-21 along with some scores of TIPI personality and education level have provided the greatest contribution to the model predictions.

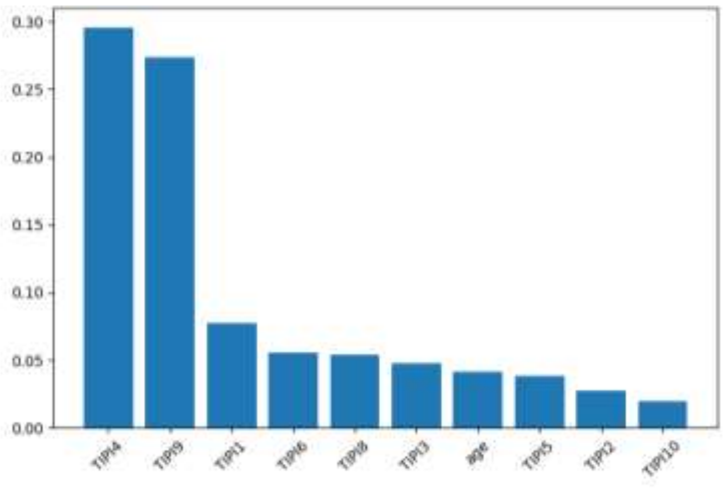

Figure 16. Relative contribution of each variable to model predictions.

Explainable AI Integration

To ensure model transparency and usability, this study incorporates Explainable AI (XAI) techniques alongside traditional machine learning methods. The Random Forest classifier provides feature importance plots, which reveal which input variables such as specific DASS-21 items, TIPI personality traits, or demographic factors have the strongest influence on predictions. Additionally, correlation heatmaps and multivariate visualizations help to uncover meaningful patterns and interactions between psychological and cognitive features.

Performance evaluation through confusion matrices and ROC curves further supports interpretability by making model accuracy and error distribution clearly visible. Together, these XAI elements improve user trust, enhance model transparency, and support responsible application of AI in sensitive health-related research.

Cross-Validation Analysis

A four-fold cross-validation strategy was used to check the stability and the generalizability of the depression risk prediction model. The classifier was trained on a different division of the data and tested on the rest of the data for every fold and the receiver operating characteristic (ROC) curve calculated as well as the confusion matrix to determine the performance.

In the initial fold, the model had a strong separation between depressed and non-depressed classes with an area under the curve (AUC) of 0.838. The respective confusion matrix validated a high true positive rate and balanced classification (Figure 17).

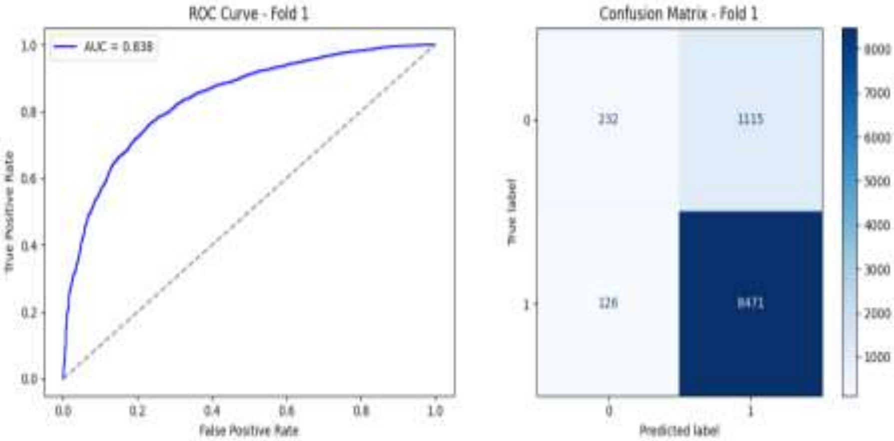

Figure 17. Performance of the depression classification model during the first cross-validation fold.

The performance was similar in the second fold and AUC was 0.832. The confusion matrix of Fold 2 supported the validity of the classifier as the error rates of misclassification were only slightly different than the ones in Fold 1 (Figure 18).

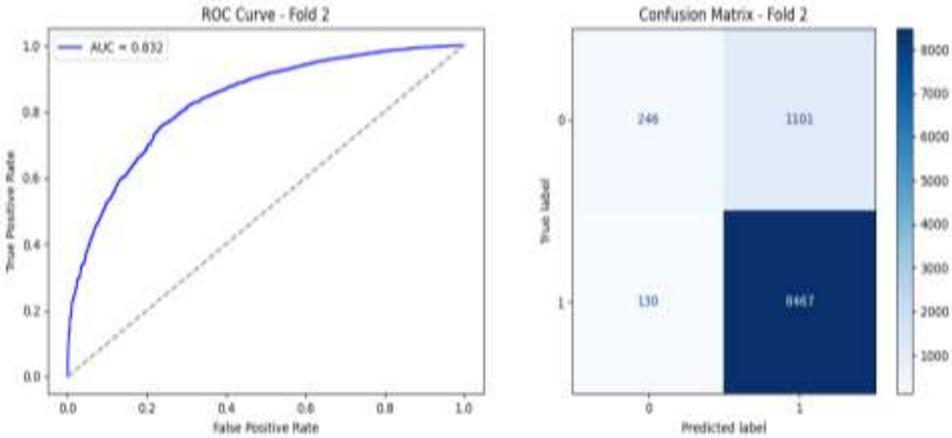

Figure 18. Performance of the depression classification model during the second cross-validation fold.

In the third fold, the results were also comparable with the AUC of 0.832. Confusion matrix of Fold 3 also proved the effectiveness of the model to detect accurately with different partitions of data (Figure 19).

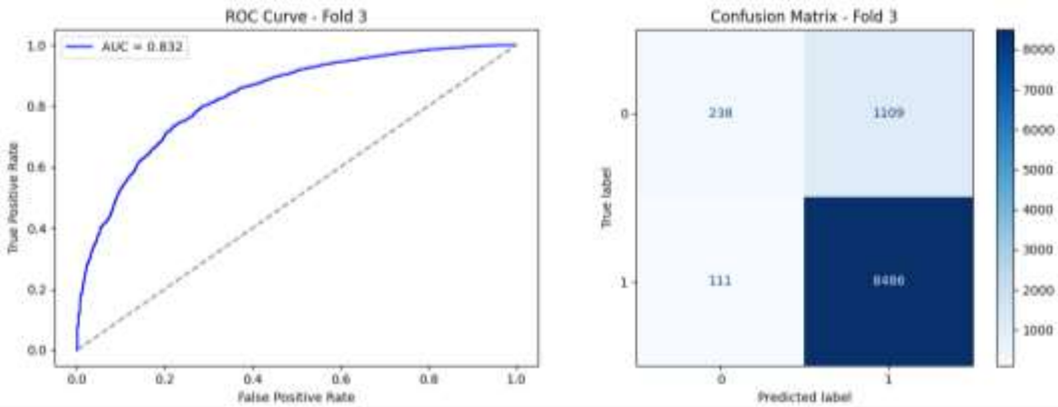

Figure 19. Performance of the depression classification model during the third cross-validation fold.

The model retained a high accuracy in the fourth and the last fold with an AUC of 0.833. Fold 4 showed the same balance of sensitivity and specificity, which confirmed the reproducibility of the machine learning method on the confusion matrix (Figure 20).

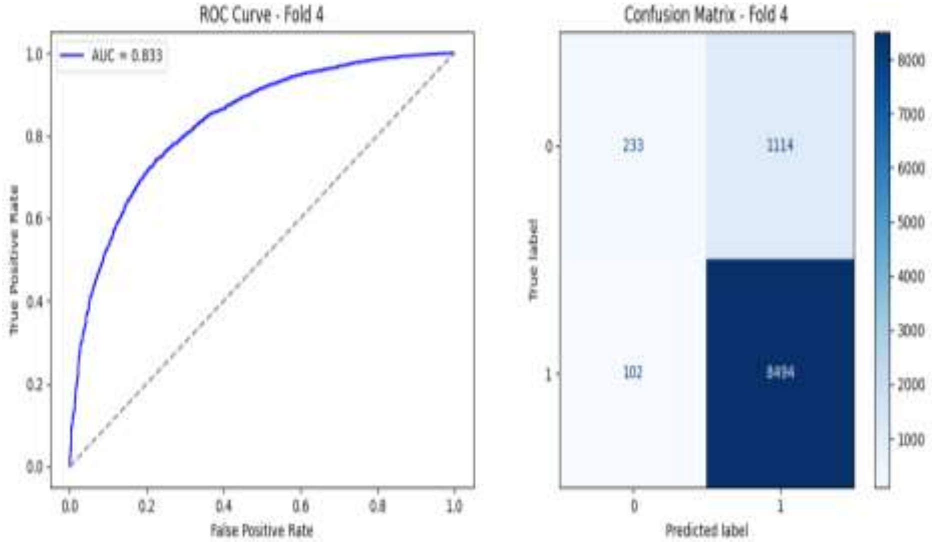

Figure 20. Performance of the depression classification model during the fourth cross-validation fold.

Together, these cross-validation results work as the evidence of the robustness and stability of the suggested AI-based depression identification framework in the context of the Gulf population of immigrants as the ROC curves and confusion matrices show consistent strong results in all folds.

Neuroimaging-Based Classification

The second important element of the dual-modality AI framework in this study was the neuroimaging-based classification. This section of the study shows how convolutional neural networks (CNNs) may be used to process brain magnetic resonance imaging (MRI) scans to distinguish between different types of tumors. The dataset involved four categories of diagnosis, namely, glioma, meningioma, pituitary tumor, and no tumor, which had different radiological patterns. Representative MRI images were provided to visually demonstrate tumor classes that were investigated in this paper.

Process of Tumor Depiction

In this study, tumor representation used a computational workflow. All MRI scans underwent preprocessing to ensure consistency. Such processes included grayscale conversion, resizing to a standard resolution, and normalization of pixel intensity in order to reduce variations due to imaging conditions. Minor rotations and flips were used to augment data in order to improve model robustness. Following preprocessing, the CNN was applied to the images, first learning simple features of edges, intensity gradients etc, and then learning complex tumor features, such as irregular shapes, and abnormal intensity regions. The model used these derived features to categorize each of the scans into one of the four diagnostic classes. The technical details of such classification pipeline will be given in Section 3.4 Model Development and Training, whereas ethical issues associated with processing sensitive MRI data are discussed further in Section 6.3 Ethical Framework.

Visualization of MRI Examples

Figure 21 shows typical MRI of the four diagnostic categories. There are eight figures with two examples per class; the variability in the presentation of tumors is shown, and these are compared to normal brain scans. The row one shows gliomas that are usually irregular and infiltrative masses with non-homogenous signal intensity. The second row displays meningiomas that appear as extra-axial lesions with clear demarcations as well as a relatively homogenous intensity. The third row depicts pituitary tumors, which are small and localized lesions located within the sellar area, revealing abnormal pattern of intensities that contrast it with the surrounding tissue. The fourth row shows normal brain images which only show proper anatomical structures and not any abnormal intensities and distortions.

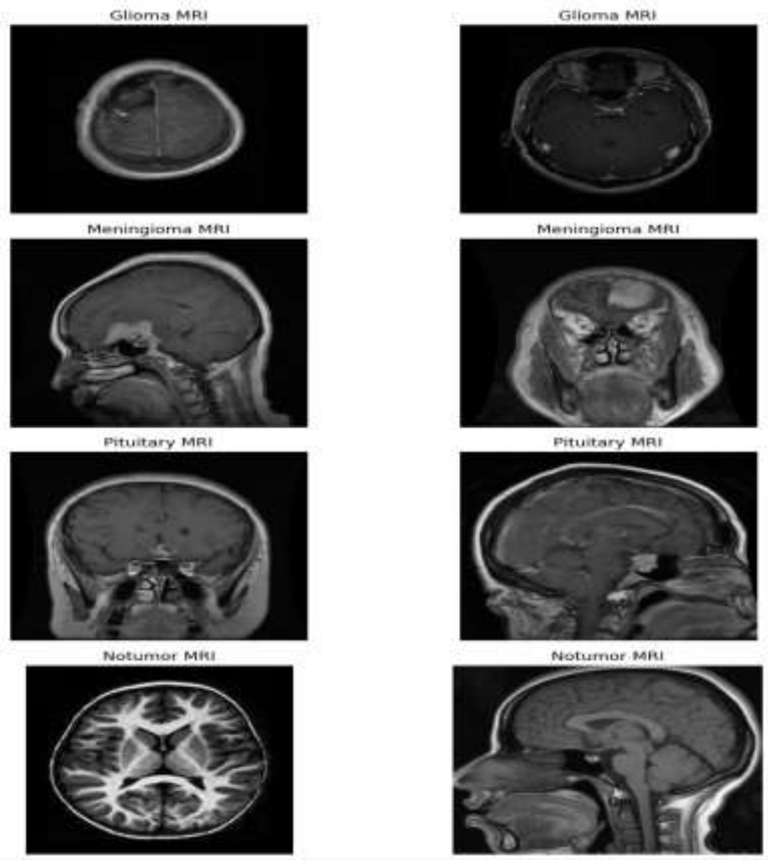

Figure 21. MRI of glioma, meningioma, pituitary tumor and normal brain.

Relevance to the Dual-Modality Framework

Figure 21 contains images that are visual representations of the tumor classes that have been examined in this study. They depict the differences between radiology of tumor types and normal anatomy of brain as evidence of the methodological description of the CNN. Although these images did not form a direct part of the quantitative assessment, they show the kind of data that the model works with, and graphically supplement the classification process, which is described in this section. Combined with the psychological information analysis, introduced above, the examples of neuroimaging provided above help to support the importance of the combination of imaging and psychological tests within a two-modality system of early identification of the risks to neurologic and mental health.

Ethical Challenges in AI Neurology and the Role of Explainable AI

Artificial intelligence (AI) has the transformative potential in neurological and mental health screening. Nevertheless, its use in areas that are deemed sensitive, like the identification of stress, depression and anxiety amid immigrant communities also poses ethical issues. In this section, the key ethical issues will be described along with the ways of how they can be resolved with the help of Explainable AI (XAI).

Ethical Challenges in AI for Mental Health Screening

Algorithmic Bias and Fairness

Artificial intelligence could reproduce bias within the data sets that it is trained on. Migrant groups are usually misrepresented in mental health data, resulting in biased forecasts and skewed results. Such bias threatens the fairness of AI-assisted diagnoses.

Privacy and Confidentiality Risks

Information relating to mental health and especially neuroimaging data and psychometric information is very sensitive. Insufficient anonymization or data misuse may subject individuals to discrimination or stigma, constituting unethical deployment of AI.

Cultural Sensitivity and Misinterpretation

Majority of the AI models are trained on Western-centric data, so they may not represent the culturally specific manifestations of mental health symptoms in immigrants. This lack of cultural adaptability can reduce diagnostic accuracy.

Stigma and Risk of Misuse

Improper or incorrect AI predictions can enforce the status quo of stigma and be misinterpreted by employers, immigration services or policymakers resulting in the disadvantage of the vulnerable groups.

Lack of Transparency and Accountability

The black-box AI models conceal their decision-making process, and therefore cannot be used to justify their results by clinicians and policymakers when they make an error.

Overcoming Ethical Challenges through Explainable AI

XAI offers ways of explaining AI decisions and making them transparent, interpretable and ethically responsibility. XAI has the potential to explain how models make the predictions through the integration of the techniques that include feature importance visualization, SHAP value explanations, and correlation-based analysis.

XAI enables developers to identify and reduce hidden biases in datasets and predictions, ensuring fairer outcomes. By revealing how features contribute to predictions, it supports culturally sensitive model adaptations. Transparent reasoning enhances the confidence of clinicians, patients, and policymakers, while interpretability allows decisions to be audited, thereby reinforcing accountability.

In this study, the inclusion of feature importance plots and interpretability visualizations represents an initial step toward responsible AI. Further expansion of XAI approaches would enhance fairness, privacy protection, and cultural sensitivity, making AI a supportive and ethically aligned tool for migrant mental health care.

ETHICAL FRAMEWORK

This study uses a fairness-based, privacy-based, culturally sensitive, transparent, and non-maleficence-focused ethical framework to achieve responsible deployment of AI in neurological and mental health screening. A heterogeneous dataset was used to train the model to reduce the bias and guarantee an equal performance in populations. The privacy and confidentiality were maintained by anonymizing all of the data and following strict data protection. Cultural sensitivity is also considered in the design of the system in that diagnostic assumptions are not made which might not hold true across various cultural backgrounds. Transparency was achieved through the documentation of the entire process of model development, and preprocessing and training of the model (discussed in Section 3.4). Lastly, the principle of non-maleficence informed the location of the AI as screening support tool rather than a diagnostic alternative, which also minimized the risk of harm caused by its misuse. The presented ethical model corresponds to global recommendations regarding the responsible use of AI and makes the suggested strategy fair, interpretable, and culturally competent among vulnerable groups. The ethical principles discussed above are operationalized within a structured framework aligned with the system's design. Figure 22 illustrates how core ethical pillars such as fairness, privacy, and cultural sensitivity are embedded across the machine learning pipeline and deployment strategy. The architecture also emphasizes explainability, non-maleficence, and responsible use, consistent with global standards for ethical AI in health settings.

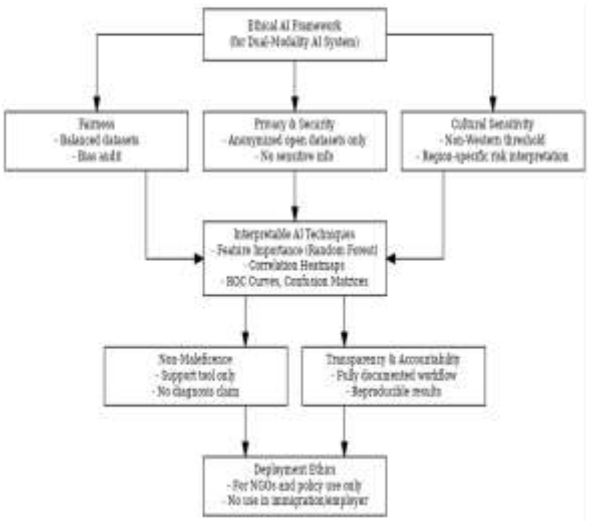

Figure 22. Ethical AI framework for dual-modality detection system

DISCUSSION

This paper introduces a thorough artificial intelligence-guided system that identifies depression, anxiety, and stress symptoms in immigrants in the Gulf nations. The study presents a dual-modality pattern of mental health screening by integration of self-reported psychological responses with demographic, personality, and cognitive measures in the form of a Random Forest model and supplementation of MRI-based classification through the use of convolutional neural networks. The metrics of high performance, accuracy (86.8%), sensitivity (96.6%), ROC-AUC (0.94) show that AI can be developed into a versatile, scalable tool that can be used to detect psychological risk in underserved populations early on.

A major lesson that can be learnt through the analysis is the national disparity in the prevalence of depression. Immigrants living in Oman and the UAE had higher rates of depressive symptoms, as is consistent in the literature, which attributes higher levels of psychological morbidity to labour policies and social exclusion in these countries (Sharma et al., 2023; Al-Maskari et al., 2011). Females and younger participants showed more significant depression scores, and this tendency was observed in international and national research (Nickson et al., 2023; McCrae et al., 2019). These trends show the necessity of demographic and gender sensitive models in the evaluation of immigrant mental health.

Addition of the personality traits and cognitive logic scores, including TIPI and VCL, was useful in enhancing the accuracy of the model in predicting. Previous studies have stressed the contribution of personal differences to the development of psychological resilience and vulnerability (Fatima et al., 2025; Rejaibi et al., 2022), and the current research confirms that the combination of psychometric data can help increase the relevance of algorithms. Additionally, the high classification accuracy in four cross-validation folds proves the model generalizability, which is a vital condition to the introduction of AI tools into real-world health systems (Aleem et al., 2022). The MRI-based part of the study complements the survey information by proving the effectiveness of multimodal AI systems. The neuroimaging model was mainly used to discriminate between tumor classes, but its implementation in the study structure is one of the examples of how various datasets could be utilized to perform neurological and psychiatric screening. This refers to the new debates that have appeared in the context of healthcare 6.0, in which multimodal, AI-advanced diagnostics are central (Varadam et al., 2024). Ethically coordinated such hybrid systems have the potential to become an assistant tool of clinicians and community health workers in migrant-driven environments. Despite these strengths, the study has several limitations. DASS-21 dataset is founded on self-reports that are subject to bias, particularly in the culturally diverse and stigmatized environment (Adu et al., 2025). Also, the lack of balanced representation of various Gulf countries in the sample might have created demographic bias, which is likely to restrict external validity. Although the MRI data was helpful in verifying technical feasibility, it had no direct correlation with a psychological condition and future research ought to investigate imaging biomarkers unique to stress or depression.

The future study should be concentrated on gathering longitudinal data to determine the development of mental health over time. An increase in the input modalities, including the speech, facial expression, or wearable sensor data, may enhance the ecological validity and engagement of users as demonstrated by Haque et al. (2018) and Hidayah et al. (2025). The other crucial point is the incorporation of explainable AI (XAI) systems, which would help these tools be more transparent and reliable, especially among clinicians and policymakers (Zogan et al., 2022; Abdelrahman, 2023). The social and technical implications of the study are both implications. Technically, it offers a reproducible, interpretable framework that is aligned with the peculiar requirements of migrant health analytics. Socially, it provides data-based information that may inform policy action, NGO initiatives, and equal access to mental health facilities in the Gulf. According to Matlin et al. (2018) and Angel (2024), digital inventions based on cultural awareness and community engagement can be used to fill the systemic gaps in mental health care. This dual-modality AI system shows that ethically informed technology can be integrated, as it helps to identify risks of mental health issues in vulnerable populations. It adds to the expanding area of computational psychiatry as well as assists global health policies towards migrants in risky areas. The integration of explainable AI (XAI) techniques such as feature importance analysis and correlation visualizations strengthens the interpretability and trustworthiness of the proposed framework. These methods ensure transparency in model decision-making, which is crucial when deploying AI in sensitive mental health contexts. Additionally, the study adheres to ethical AI practices by addressing potential bias, ensuring cultural sensitivity, and emphasizing the supportive, not diagnostic role of the system. Together, these considerations enhance the framework's suitability for use in real-world public health interventions aimed at migrant populations.

CONCLUSION

This paper shows a dual-modality AI-assisted system to detect stress, depression, and anxiety symptoms among the immigrant community in Gulf countries based on both neuroimaging data and psychological questionnaires. The model is accurate and interpretable by combining the responses on DASS-21 with demographic, personality (TIPI), and cognitive (VCL) characteristics in a supervised machine learning pipeline, and complementing that with convolutional neural network-based analysis of MRI images. These results corroborate the potentiality of scalable data-driven mental health screening tools that may be specifically designed to assess the particular vulnerability of migrant communities. The analysis showed clear geographic patterns as UAE and Oman had a higher prevalence of depressive symptoms, which was due to the sociopolitical conditions and stressors in the workplace. The high methodological rigor of the Random Forest and CNN model and the reliability of cross-validation demonstrate the quality of the method and its prospects of real-life application. At the same time, the study emphasizes that ethical safeguards, supported by explainable AI, are indispensable to ensure fairness, transparency, and cultural sensitivity in the deployment of these technologies. Although the framework is not suggested to substitute clinical diagnosis, it provides a cost-effective and ethically acceptable method of the early identification of mental health risks in low-resource countries. The system is useful to NGOs, mobile health platforms and public agencies engaged in mental health advocacy, particularly in policy-sensitive and multicultural settings. It also provides possibilities of culturally contextual and technically explicable digital mental health interventions. Further research should aim at incorporating longitudinal data, increasing the types of input, including speech and wearable sensors, as well as incorporating parts of explainable AI (XAI) to enhance transparency and clinical trust. This study can provide a comprehensive model of the application of artificial intelligence to the improvement of mental health equity, which enables the implementation of an empirical approach to addressing the health needs of immigrants in vulnerable and underserved areas.

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