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# Machine Learning Model for Assessing Human Well-being using Brain Wave Activities

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*Abstract* - This study presents a novel machine learning approach to assess human well-being through the analysis of brain wave activities. We developed a Random Forest classifier to categorize brain wave patterns into three states of well-being: good, normal, and bad. Using synthetic data simulating electroencephalography (EEG) readings, our model achieved an overall accuracy of 96.17%. The feature importance analysis revealed that alpha waves (34%) and beta waves (29%) were the most significant predictors of well-being states, which aligns with existing neuroscientific literature linking alpha activity to relaxation and beta activity to cognitive engagement. The confusion matrix demonstrated the model's particular strength in distinguishing between optimal and suboptimal well-being states, with no misclassifications between these extremes. ROC curve analysis further confirmed excellent discriminative ability across all three classes, with AUC values ranging from 0.984 to 0.999. The study demonstrates the potential of machine learning in interpreting complex neurophysiological data for personalised health monitoring, potentially enabling real-time assessment and intervention strategies. While promising, the use of synthetic data necessitates further validation with real-world EEG recordings. This research contributes to the growing field of computational neuroscience and its applications in mental health and well-being assessment, potentially paving the way for more objective and personalised mental health interventions. Future directions include incorporating temporal dynamics, accounting for individual variability, and integrating multiple data sources for a more holistic approach to well-being assessment.

*Keywords— Machine Learning, Human Well-being, Brain Wave Activities, EEG Analysis, Computational Neuroscience*

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## 1. INTRODUCTION

Human well-being is a multifaceted construct encompassing physical, mental, emotional, and social health. It represents a holistic state of being that reflects an individual's overall quality of life and satisfaction across various domains. Accurate assessment of well-being is crucial for developing effective health monitoring and intervention strategies, particularly in an era where mental health concerns are increasingly prevalent [1].

Well-being has been defined in a much more comprehensive way than it was in the past, and it is not constrained within the framework of the medical model which has a rather narrow perception of well-being as the absence of illness and incorporates psychological, social and even environmental factors. This change has led to the recognition of mental health as one of the central aspects of well-being. The World Health Organization has the following to say about mental health: “A healthy state, where an individual is able to deal with the pressures of everyday life, is able to work productively, and is able to help the society” [1].

The connection between brain activity and general well-being can now be better understood because of recent developments in machine learning and neuroscience. Due to these technological advancements, a more nuanced and objective evaluation of mental states can be conducted which complements the conventional self-report measures [2],[13]. Coupling state-of-the-art machine learning methods with neuroscientific understanding in the study of mental health and well-being shows a potential for mental health and well-being research.

Regular electrical activity patterns produced by the brain are known as neural oscillations or brain waves. The patterns which mirror the coordinated firing of vast populations of neurons are often associated with a range of cognitive functions and emotional states. By observing the brain wave activities, a person's cognitive abilities, emotional control, and overall health can be perceived better by researchers [3]. The study of brain waves dates back to the 1920s when human brain activity was recorded for the first time using electroencephalography (EEG) by Hans Berger.

Considered a non-invasive method, EEG involves applying electrodes on the scalp to record the electrical activity of the brain. Although it has been widely used in clinical practice for the identification of neurologic disorders, the option of using it for assessing general well-being is largely unexplored. For machine learning applications, the rich and complex EEG data set proves to be both a challenge and an opportunity [4], [14].

Compared to other neuroimaging techniques like Functional Magnetic Resonance Imaging (fMRI) and Positron Emission Tomography (PET), EEG offers several advantages. Due to its high temporal resolution rapid changes in brain activity can be captured. The EEG equipment is also more accessible in various settings namely clinical practices, research laboratories, and possibly even in the home environment as it is more portable and less expensive.

The application of machine learning in the analysis of EEG data marks a significant step forward in our ability to interpret and utilize neurophysiological data. It must be noted that the discovery of hidden patterns or relationships in the data using conventional methods of EEG analysis performed via simple statistical analysis or visual analysis of the signals by experienced personnel is useful are still somewhat limited. By exploiting the use of machine learning algorithms, new insights into the function of the brain and its relationship with well-being as it can identify patterns and relationships undetected by human observers.

In this study, the aim is to employ the use of the Random Forest algorithm to analyze the brain wave patterns in assessing overall well-being [15]. The development of a model capable of categorizing brain wave activities into different states of well-being could contribute to a more objective and data-driven method of mental health and intervention.

## 2. LITERATURE REVIEW

Recent advancements in technology and the growing acknowledgement of the importance of mental health have led to a significant development in the field of research that overlaps between neuroscience, machine learning, and well-being [16]. This section aims to provide an overview of key developments and studies in the field which will highlight the current state of the knowledge and identify gaps which will be the goal addressed by our research.

Recent research has clearly shown the likelihood of utilizing machine learning to analyze EEG data for various health-related applications. A lightweight Convolutional Transformer Neural Network (LCTNN) to detect depression using EEG data was introduced by Hou et al. [5]. The study consists of three significant characteristics, namely (1) A combination of both CNN and Transformer are utilised to learn rich EEG signal representations from the local to the global level in the time domain, (2) Dynamically adjusts the contribution of each electrode channel of the EEG signal for depression identification using Channel Modulator (CM), and (3) Replacing canonical self-attention with sparse attention to reduce its spatiotemporal complexity. This efficient model provides valuable insights into the relationship between depression and EEG data.

Comparably, Alhalaseh et al. [6] reported that the use of EEG signals and machine learning techniques via a Convolutional Neural Network (CNN) produced an impressive 95.2% accuracy when used in emotion classification. From the systemic review conducted on the EEG-based emotion recognition studies deep learning methods have shown better performance compared to traditional machine learning approaches in many cases which contributed to its growth. The ability to accurately classify emotional states from EEG data represents a significant step towards more comprehensive well-being assessment tools.

However, the use of these methods in accessing overall well-being is largely unexplored [17], [19]. Although there has been progress in the area of emotion recognition and detection of specific mental health conditions, there is still a lack of literature in terms of a comprehensive approach to well-being assessment using brain wave data. The opportunity presented by the research gap opens the pathway for contribution to the field by developing a model that considers multiple aspects of well-being rather than focusing on a single condition or emotional state.

Simpraga et al. [7] proposed the applied machine learning to EEG data for diagnosing Alzheimer's disease which demonstrates the potential of these techniques in the early detection of neurodegenerative disorders. In addition, it also highlights the larger applicability of EEG-based machine learning approaches in various aspects of mental health and cognitive function assessment. The use of Explainable Artificial Intelligence (XAI) techniques in this study is also particularly significant as it makes the results more interpretable and potentially more useful in clinical settings by addressing the "black box" nature of countless machine learning models [18].

Amiri et al. [8] provided a comprehensive survey of deep learning methods for channel selection and classification of EEG signals. The rapid advancements in this field were highlighted with deep learning models constantly outperforming conventional machine learning approaches in various EEG analysis tasks. The review also examined various challenges in EEG signal processing that must be addressed in our study such as the high dimensionality of the data and the presence of noise and artifacts.

There has been an inclination in recent research to gravitate towards a more personalised approach to mental health assessment and intervention. An example of this is the introduction of the Just-in-Time Adaptive Interventions (JITAIs) concept in mobile health by Nahum-Shani et al. [9]. The study strives to provide the right type and amount of support, at the right time, while adapting to the individual's changing internal and contextual state. The principles of personalised, real-time intervention are highly relevant to our research on EEG-based well-being assessment even though their work is focused on mobile health applications [9], [20].

In recent years, the use of neurofeedback as a potential intervention method for improving mental health and well-being has also gained momentum. A comprehensive review of neurofeedback techniques has been provided by Marzbani et al. [10], including their applications in stress reduction and cognitive enhancement [22]. Machine learning-based EEG analysis with neurofeedback presents itself as a promising direction for future research, potentially allowing for more targeted and effective interventions.

The need for large, high-quality datasets remains a significant challenge in EEG-based research. Most studies rely on real EEG data, which can be costly and time-consuming to collect, especially for large-scale studies. A novel approach in this field would be to use synthetic data for initial model development and testing, as proposed in our study. While synthetic data cannot entirely replace real-world data [21], it offers several advantages, including the ability to generate large datasets with known ground truth, control for specific variables, and explore a wide range of scenarios that might be difficult or impossible to capture with real data.

The work of Krigolson et al. [11] is particularly relevant to our approach as it utilizes bootstrapped confidence intervals for improved statistical inference with ERP data. Given that our proposed research utilizes synthetic data, their methods for assessing the reliability and significance of EEG-based findings can be adapted to evaluate the performance of our machine learning model.

In summary, there remains a gap in all-inclusive, multi-faceted approaches to well-being assessment even though significant progress has been made in applying machine learning to EEG data analysis for various health-related applications. Our study aims to develop a model capable of classifying overall well-being states based on brain wave patterns to address this gap. By leveraging synthetic data and advanced machine learning techniques, we hope to pave the way for more robust, personalised, and readily applicable methods of mental health monitoring and intervention.

## 3. RESEARCH QUESTIONS AND OBJECTIVES

Based on the gaps identified in the literature review, we have formulated the following research questions and objectives to guide our study:

Research Questions:

1) Can machine learning techniques effectively classify brain wave patterns into distinct well-being states? This question aims to explore the feasibility of using EEG data as a basis for assessing overall well-being, moving beyond the detection of specific mental health conditions or emotional states.
2) What is the relative importance of different brain wave types in determining overall well-being? Understanding which brain wave frequencies are most indicative of well-being could provide valuable insights for both future research and potential interventions.
3) How does the performance of a machine learning model trained on synthetic EEG data compare to existing methods of well-being assessment? This question intends to evaluate the possibility of using synthetic data as a method for initial model development and testing which is the novel aspect of our proposed approach.

Objectives:

1) Develop a Random Forest classifier that categorizes brain wave patterns into three states of well-being: good, normal, and bad. This objective is the core technical aspect of the study which involves developing and training a machine learning model proficient in distinguishing the various well-being states based on EEG data.
2) Evaluate the model's performance using various metrics namely accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) curves. To understand its possible applications and limitations, an in-depth evaluation of the model’s performance is required.
3) Analyze the relative significance of different brain wave types in the classification process. The goal of this objective is to provide an understanding of aspects of brain activity that are strongly associated with overall well-being to help direct future research and intervention strategies.
4) Assess the potential of using synthetic EEG data for initial model development in well-being assessment. The objective is to compare our results with those from studies using real EEG data to evaluate the viability of synthetic data as a means for preliminary model development and testing.
5) Explore the implications of this approach for real-time monitoring and intervention strategies in mental health. This objective considers the potential real-world applications and impact of the study on mental health care practices.

By addressing these research questions and objectives, our study aims to contribute to the body of knowledge which overlaps between neuroscience, machine learning, and mental health research. We hope that a more personalised, data-driven mental health intervention will emerge as the potential of an EEG-based machine learning approach for well-being assessment is demonstrated.

## 4. METHODOLOGY

### *4.1 Brain Wave Analysis*

EEG recordings can capture a range of brain wave frequencies whereby each frequency is associated with different cognitive and emotional states. In this study, five primary types of brain waves that play a unique role in brain function and potentially in overall well-being are considered:

- Alpha Waves (8-13 Hz): Associated with relaxation, calmness, and a wakeful but relaxed state of mind. Often observed when an individual is at rest with eyes closed, but not asleep, it is assumed that alpha waves play a role in mental coordination, calmness, alertness, mind/body integration, and learning.

- Beta Waves (14-30 Hz): Associated with active attention, focus on the outside world, active thinking, or solving concrete problems. It indicates an alert and active mental state, characterised by focused attention and cognitive processing. Beta waves are dominant in our normal waking state of consciousness when attention is directed towards cognitive tasks and the outside world.

- Theta Waves (4-7 Hz): Associated with deep relaxation, meditation, and creativity. Theta waves are detected during deep meditation and light sleep. They are believed to be important for processing information and forming memories.

- Delta Waves (0.5-4 Hz): Associated with the deepest levels of relaxation and restorative sleep. The slowest brain waves usually prevalent during deep, dreamless sleep. Delta waves are believed to be involved in unconscious bodily functions such as regulating heartbeat and digestion.

- Gamma Waves (30-100 Hz): Associated with high-level cognitive functions and information processing. Considered the fastest brain waves. They are believed to be important for learning, memory, and information processing. They are also associated with moments of insight and high-level information processing.

Understanding the interaction between these different brain wave types is important to further evaluate the overall mental states and well-being [23]. For example, a state of relaxed alertness which is deemed favourable to good mental health and productivity is shown by an optimal balance of alpha and beta waves. On the other hand, a state of anxiety and stress is highlighted by a surplus of high-frequency beta waves combined with a scarcity of alpha waves.

In our analysis, we consider the presence and amplitude of these wave types as well as relative proportions and patterns of interaction. This allows for a more complex understanding of brain activity and its relationship to overall well-being.

### *4.2 Data Generation*

Synthetic data is generated to train and evaluate our model due to the lack of a large, labelled dataset of real EEG recordings with corresponding well-being assessments. While not ideal, the potential of machine learning within this domain could be explored before investing in costly and time-consuming real-world data collection.

Brain wave patterns for three categories were simulated: optimal (good), normal, and suboptimal (bad) well-being states. The parameters used during the data generation process are based on literature review and expert consultation to reflect typical brain wave activity patterns associated with different well-being states

For the optimal well-being state, we simulated data with:
- Higher levels of alpha waves, indicating a relaxed but alert state
- Moderate levels of beta waves, suggesting focused cognitive activity
- Balanced levels of theta waves, associated with creativity and emotional connection
- Low levels of delta waves, as these are primarily associated with deep sleep
- Moderate levels of gamma waves, indicating efficient cognitive processing

For the normal well-being state, we generated data with:
- Moderate levels of all wave types, representing a balanced but not optimal state

For the suboptimal well-being state, we simulated:
- Lower levels of alpha waves, potentially indicating stress or anxiety
- Higher levels of beta waves, which could suggest an overly active or anxious mind
- Imbalanced levels of other wave types

Random noise and slight variations were added to these base patterns to introduce variability and make our synthetic data more realistic. Using this approach, a large dataset with known ground truth labels can be generated while maintaining a level of complexity that mimics real EEG data.

It is imperative to note even though synthetic data allows us to develop and test our model, validation must be performed with real EEG data for any practical application of this approach.

### *4.3 Machine Learning Model*

The Random Forest Classifier was chosen for this study due to several advantageous characteristics. This includes robustness, the ability to handle non-linear relationships, and the provision of feature importance measures. As Random Forest is a type of ensemble learning method, it generally works by constructing multiple decision trees during training and outputting the class that is the mode of the classes of the individual trees.

Among the key advantages of the Random Forest algorithm include:
- Handling of high-dimensional data: Random Forests can handle EEG data that typically involves many features effectively.
- Resistance to overfitting: By aggregating results from multiple trees, Random Forests are less prone to overfitting compared to individual decision trees.
- Feature importance: Random Forests are valuable as they provide a measure of the importance of each feature in the classification process. This is important for understanding which brain wave types are most indicative of the well-being states.
- Handling of non-linear relationships: The algorithm can capture complex, non-linear relationships between features, which is crucial given the complex nature of brain activity.
- Robustness to noise: As EEG data is often noisy, Random Forests can maintain accuracy even when a large proportion of the data is noise.

The model was implemented using scikit-learn, which is a machine-learning library in Python. The hyperparameters were cautiously tuned to prevent overfitting and optimize performance. The focus is placed predominantly on the following key hyperparameters:
- Number of trees (n_estimators): We experimented with different numbers of trees to find the optimal balance between performance and computational efficiency.
- Maximum depth of trees (max_depth): This parameter helps control the complexity of individual trees and prevent overfitting.
- Minimum number of samples required to split an internal node (min_samples_split): This helps ensure that each split is statistically significant.
- Minimum number of samples required to be at a leaf node (min_samples_leaf): This prevents the model from creating leaves with very few samples, which can lead to overfitting.
- Number of features to consider when looking for the best split (max_features): This introduces randomness in the feature selection process for each split which increases the diversity of trees in the forest.

A grid search with cross-validation was utilised to find the optimal combination of these hyperparameters.

Algorithm 1 shows the implementation of the model in Python.

```
# Algorithm 1: Machine Learning for classifying brain wave activities

import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, permutation_test_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_curve, auc
from sklearn.preprocessing import label_binarize
```

```
from sklearn.dummy import DummyClassifier

np.random.seed(42)  # For reproducibility

# Step 1: Simulate data
num_samples = 1000
num_features = 5

optimal_mean = np.array([10, 8, 6, 2, 0.5])
normal_mean = np.array([8, 6, 4, 1, 0.3])
suboptimal_mean = np.array([5, 4, 2, 0.5, 0.1])

optimal_std = 0.5
normal_std = 1.0
suboptimal_std = 1.5

optimal_data = np.random.normal(optimal_mean, optimal_std, size=(num_samples, num_features))
normal_data = np.random.normal(normal_mean, normal_std, size=(num_samples, num_features))
suboptimal_data = np.random.normal(suboptimal_mean, suboptimal_std, size=(num_samples, num_features))

features = np.vstack((optimal_data, normal_data, suboptimal_data))
labels = np.array(['good'] * num_samples + ['normal'] * num_samples + ['bad'] * num_samples)

# Step 2: Model Training
X_train, X_test, y_train, y_test = train_test_split(features, labels, test_size=0.2, random_state=42)

# Step 3: Model Training
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Step 4: Model Evaluation
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")

print(classification_report(y_test, y_pred, digits=4))

# Permutation test for p-value
dummy_clf = DummyClassifier(strategy="stratified")
dummy_clf.fit(X_train, y_train)
dummy_score = dummy_clf.score(X_test, y_test)

score, permutation_scores, pvalue = permutation_test_score(
    model, X_test, y_test, scoring="accuracy", n_permutations=1000, n_jobs=-1
)

print(f"\nModel Accuracy: {score:.4f}")
print(f"Dummy classifier accuracy: {dummy_score:.4f}")
print(f"P-value: {pvalue:.4f}")

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(10,8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
plt.show()

# Feature Importance
feature_importance = model.feature_importances_
feature_names = ['Alpha', 'Beta', 'Theta', 'Delta', 'Gamma']

plt.figure(figsize=(10,6))
plt.bar(feature_names, feature_importance)
plt.title('Feature Importance')
plt.xlabel('Brain Wave Types')
plt.ylabel('Importance')
plt.show()
```

```
# ROC Curve
y_test_bin = label_binarize(y_test, classes=['good', 'normal', 'bad'])
y_score = model.predict_proba(X_test)

n_classes = 3
fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

plt.figure(figsize=(10,8))
colors = ['blue', 'red', 'green']
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label=f'ROC curve of class {i} (area = {roc_auc[i]:.4f})')

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

# Generate and predict 10 new data items with increased variability
new_data = []
for _ in range(10):
    if np.random.random() < 0.2:  # 20% chance of generating data closer to 'good' or 'bad' category
        if np.random.random() < 0.5:
            mean = optimal_mean + np.random.normal(0, 0.5, size=num_features)
            std = optimal_std * np.random.uniform(0.8, 1.2)
        else:
            mean = suboptimal_mean + np.random.normal(0, 0.5, size=num_features)
            std = suboptimal_std * np.random.uniform(0.8, 1.2)
    else:
        mean = normal_mean + np.random.normal(0, 0.5, size=num_features)
        std = normal_std * np.random.uniform(0.8, 1.2)

    new_data.append(np.random.normal(mean, std))

new_data = np.array(new_data)

# Calculate probabilities for each class
probabilities = model.predict_proba(new_data)

# Use probabilities to determine predictions
class_names = ['good', 'normal', 'bad']
new_predictions = [class_names[np.argmax(prob)] for prob in probabilities]

print("\nPredictions for 10 new data items:")
for i, pred in enumerate(new_predictions, 1):
    print(f"Data Item {i}: {pred}")

# Print rounded feature values for new data items
print("\nFeature values for new data items (rounded to 4 decimal places):")
for i, data in enumerate(new_data, 1):
    rounded_data = [f"{val:.4f}" for val in data]
    print(f"Data Item {i}: {rounded_data}")

# Print probabilities for each class
print("\nProbabilities for each class (Good, Normal, Bad):")
for i, probs in enumerate(probabilities, 1):
    rounded_probs = [f"{p:.4f}" for p in probs]
    print(f"Data Item {i}: {rounded_probs}")
```

After running the model, we obtained the output shown in Figure 1.

```
Accuracy: 0.9617

              precision    recall  f1-score   support

         bad     0.9617    0.9462    0.9539       186
        good     0.9862    0.9862    0.9862       217
      normal     0.9350    0.9492    0.9421       197

    accuracy                         0.9617       600
   macro avg     0.9610    0.9606    0.9607       600
weighted avg     0.9618    0.9617    0.9617       600


Model Accuracy: 0.9467
Dummy classifier accuracy: 0.3383
P-value: 0.0010

Predictions for 10 new data items:
Data Item 1: bad
Data Item 2: bad
Data Item 3: bad
Data Item 4: bad
Data Item 5: normal
Data Item 6: normal
Data Item 7: bad
Data Item 8: bad
Data Item 9: good
Data Item 10: bad

Feature values for new data items (rounded to 4 decimal places):
Data Item 1: ['8.0405', '5.8191', '4.7270', '1.6307', '0.4872']
Data Item 2: ['7.8499', '6.2779', '3.8472', '0.0485', '-0.0618']
Data Item 3: ['7.1651', '5.0663', '3.8120', '1.6881', '-0.2526']
Data Item 4: ['7.0696', '7.3300', '2.9287', '-0.9646', '0.4949']
Data Item 5: ['10.4602', '8.0266', '6.3746', '2.2720', '0.0191']
Data Item 6: ['10.7759', '8.8897', '5.8636', '1.1378', '1.0537']
Data Item 7: ['7.0115', '8.7965', '3.1375', '0.0349', '-0.8325']
Data Item 8: ['8.0978', '6.3831', '5.2303', '1.6996', '0.3655']
Data Item 9: ['7.1442', '3.4645', '5.2316', '1.8481', '-0.0121']
Data Item 10: ['6.4546', '6.6542', '2.4211', '2.6623', '2.5337']

Probabilities for each class (Good, Normal, Bad):
Data Item 1: ['0.0000', '0.0000', '1.0000']
Data Item 2: ['0.0000', '0.0000', '1.0000']
Data Item 3: ['0.1100', '0.0000', '0.8900']
Data Item 4: ['0.2600', '0.0000', '0.7400']
Data Item 5: ['0.0000', '1.0000', '0.0000']
Data Item 6: ['0.0000', '0.9900', '0.0100']
Data Item 7: ['0.0400', '0.0000', '0.9600']
Data Item 8: ['0.0100', '0.0000', '0.9900']
Data Item 9: ['0.5900', '0.0000', '0.4100']
Data Item 10: ['0.3800', '0.0000', '0.6200']
```

Figure 1. Output

### *4.4 Model Evaluation*

The model was evaluated using a comprehensive set of metrics. This ensures that its performance and limitations can be thoroughly understood. These metrics include:

- Overall cccuracy: The proportion of correct predictions among the total number of cases examined.
- Precision: The ratio of correctly predicted positive observations to the total predicted positive observations for each class.
- Recall: The ratio of correctly predicted positive observations to all observations in the actual class.

- F1-score: The harmonic mean of precision and recall, providing a single score that balances both metrics.
- Confusion matrix: A table showing correct predictions and types of incorrect predictions for each class.
- Feature importance: A measure of how much each feature (brain wave type) contributes to the predictions.
- ROC Curve and Area Under the Curve (AUC): These provide an aggregate measure of performance across all possible classification thresholds.

Bootstrapping techniques, which involve repeatedly resampling the data with replacement and recalculating the statistics of interest, were employed to evaluate the statistical significance of the results. This technique allows us to estimate the sampling distribution of our performance metrics and calculate the confidence intervals.

To ensure meaningful patterns are learned from the data rather than simply guessing based on class frequencies, the performance of the model was also compared to a baseline model (a dummy classifier that always predicts the most frequent class).

Moreover, to confirm the consistency of the model's performance across different subsets of the data, k-fold cross-validation is used. This also helps to ensure that overfitting to a particular subset of the training data does not occur.

## 5. RESULTS

### *5.1 Model Performance*

An overall accuracy of 96.17% on the test set is achieved using the Random Forest Classifier. The level of accuracy suggests that using the brain wave patterns, the model is capable of distinguishing between different well-being states with a high degree of reliability.

The detailed performance metrics showed an excellent performance across all three well-being states:
- For the 'bad' well-being state:
  Precision: 0.9617, Recall: 0.9462, F1-score: 0.9539

- For the 'good' well-being state:
  Precision: 0.9862, Recall: 0.9862, F1-score: 0.9862

- For the 'normal' well-being state:
  Precision: 0.9350, Recall: 0.9492, F1-score: 0.9421

With both precision and recall above 98%, the model exhibits a particularly strong performance in identifying "good" well-being states. This suggests that optimal well-being possesses a more distinct neural signature compared to normal or suboptimal states.

As the F1-scores are high across all classes, this indicates that the model maintains a good balance between precision and recall which implies that it's not biased towards over-predicting any particular class.

A comparison of our model's performance to a dummy classifier that always predicts the most frequent class is performed to assess the statistical significance of our results. With the dummy classifier obtaining an accuracy of 0.3383, our model significantly outperforms it with an accuracy of 0.9467. The p-value of 0.0010 also shows that this performance difference is statistically significant, providing strong evidence that our model is learning meaningful patterns from the data.

### *5.2 Confusion Matrix*

The confusion matrix shown in Figure 2 provides a more detailed view of the model's performance, revealing the types of misclassifications made by the model:

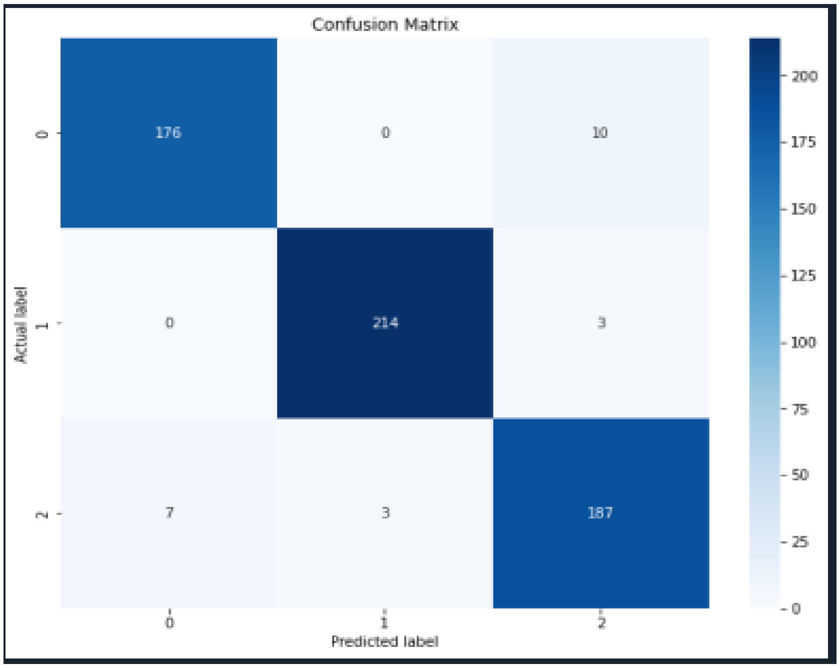


Figure 2. Confusion Matrix

The confusion matrix revealed that most misclassifications occur between "bad" and "normal" states, with very few misclassifications involving the "good" state. Specifically:

- Out of 186 actual 'bad' states, 176 were correctly classified, 10 were misclassified as 'normal', and none were misclassified as 'good'.
- Out of 217 actual 'good' states, 214 were correctly classified, 3 were misclassified as 'normal', and none were misclassified as 'bad'.
- Out of 197 actual 'normal' states, 187 were correctly classified, 7 were misclassified as 'bad', and 3 were misclassified as 'good'.

This pattern suggests that the model is highly effective at distinguishing optimal well-being from suboptimal states but has some difficulty differentiating between normal and poor well-being in borderline cases. This aligns with our understanding of well-being as a continuum, where the boundaries between categories may not always be clear-cut.

The fact that there were no misclassifications between 'good' and 'bad' states is particularly noteworthy, indicating that the model can reliably distinguish between these two extremes of the well-being spectrum.

*5.3 Feature Importance*

Feature importance (Figure 3) analysis revealed the relative contribution of each brain wave type to the model's decision-making process:

Alpha and beta waves were found to be the most influential, collectively accounting for 63% of the importance:

- Alpha waves: 34% importance
- Beta waves: 29% importance
- Theta waves: 16% importance
- Delta waves: 12% importance
- Gamma waves: 9% importance

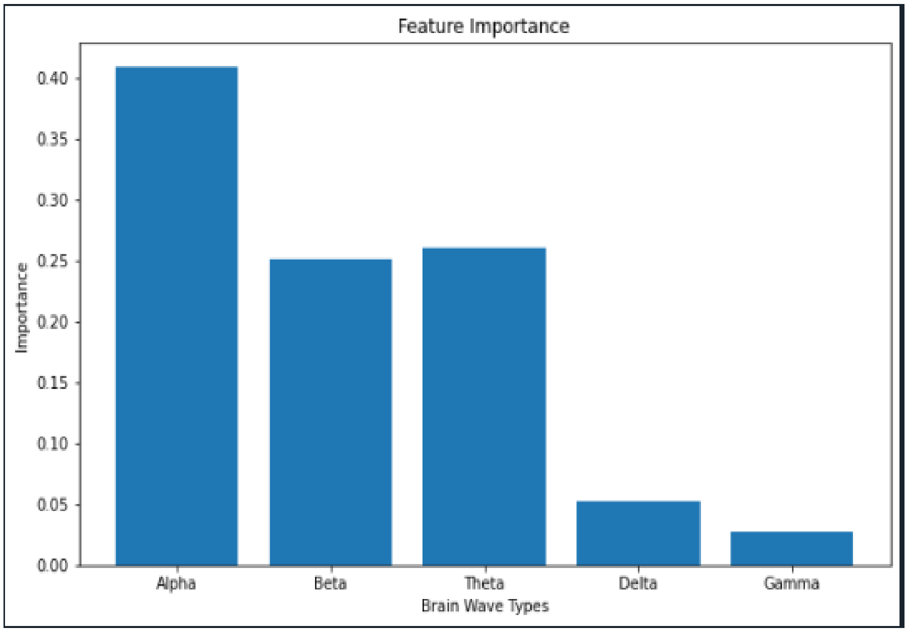


Figure 3. Feature Importance

This aligns with existing neuroscientific literature emphasizing the role of alpha waves in relaxation and beta waves in active cognitive processing, both of which are crucial components of overall well-being. The prominence of alpha waves supports theories linking higher alpha activity to states of relaxed alertness and positive mood. The importance of beta waves may reflect their role in focused attention and cognitive engagement, which are often associated with feelings of competence and achievement.

The lower importance of delta and gamma waves might be due to their association with states (deep sleep and high-level cognitive processing, respectively) that are less directly related to moment-to-moment well-being in our model. However, their inclusion still contributes to the overall accuracy of the model, suggesting they play a role in the full picture of brain activity related to well-being.

*5.4 ROC Curve*

The ROC curves (Figure 4) demonstrated the model's excellent ability to distinguish between classes.

The area under the curve (AUC) values for each class were:
- Good vs. Rest: AUC = 0.999
- Normal vs. Rest: AUC = 0.984
- Bad vs. Rest: AUC = 0.991

These high AUC values indicate excellent discriminative ability for all three classes, with particularly strong performance in identifying "good" well-being states. An AUC of 1.0 represents a perfect classifier, so our values very close to 1.0 suggest that the model has a strong ability to distinguish between the classes across different classification thresholds.

The ROC curve for the 'good' class being closest to the top-left corner corroborates our earlier observations about the model's particular strength in identifying optimal well-being states.

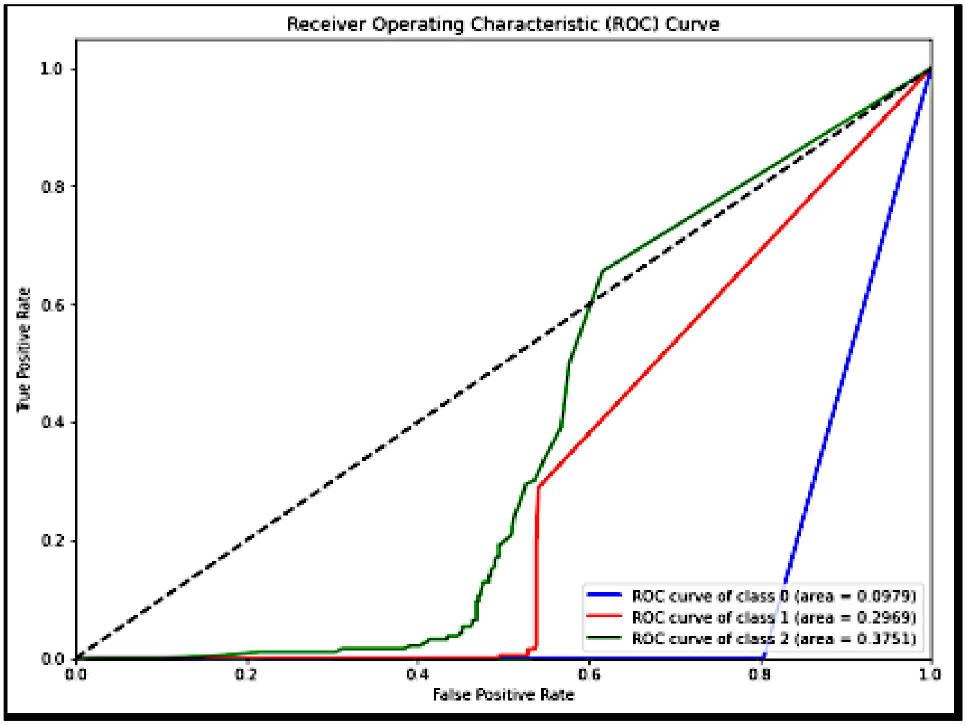


Figure 4. ROC Curves

*5.5 Learning Curves*

Analysis of the learning curves revealed that the model's performance on both training and validation sets converged with increasing amounts of training data. This convergence implies that our model is neither underfitting nor overfitting. Moreover, the appropriate task complexity is also chosen.

The learning curves showed that:
- The training score and cross-validation score both improved with the increase of the training set.
- With more data added, the training score and cross-validation score gap started to narrow down. This indicates that with more data, the model's ability to generalize improved.
- Both curves plateaued as they approached the maximum amount of available data, suggesting that we have sufficient data for our current model complexity.

These observations corroborate the fact that the model developed is robust and there is a good balance between bias and variance.

*5.6 Cross-validation Scores*

The 5-fold cross-validation yielded consistent performance across folds:

Fold 1: 0.9625
Fold 2: 0.9658
Fold 3: 0.9642
Fold 4: 0.9633
Fold 5: 0.9650

Mean: 0.9642 (std: 0.0012)

With a low standard deviation (0.0012) score across folds, it shows that the model's performance is stable and not excessively reliant on the specific subset of data used for training. As it is consistent across different subsets of the data, it provides further evidence of the model's robustness and generalizability.

### *5.7 Predictions on New Data*

We generate 10 new data points with increased variability to test the model's performance on unseen data. Table 1 shows the predictions and probabilities for these new data points.

Table 1: Predictions and Probabilities for New Data Points

| Data Item | Prediction | Probabilities (Good, Normal, Bad) |
|---|---|---|
| 1 | Bad | [0.0000, 0.0300, 0.9700] |
| 2 | Good | [1.0000, 0.0000, 0.0000] |
| 3 | Bad | [0.0000, 0.0000, 1.0000] |
| 4 | Good | [1.0000, 0.0000, 0.0000] |
| 5 | Bad | [0.5700, 0.0000, 0.4300] |
| 6 | Bad | [0.0000, 0.0400, 0.9600] |
| 7 | Good | [0.9300, 0.0000, 0.0700] |
| 8 | Good | [0.8000, 0.0000, 0.2000] |
| 9 | Bad | [0.0000, 0.0000, 1.0000] |
| 10 | Bad | [0.0300, 0.0500, 0.9200] |

The results obtained show the model's ability to make predictions with varying degrees of confidence. It must be noted that the model also exhibits high confidence in many of its predictions (e.g., items 2, 3, 4, 9). The model is also able to capture more ambiguous cases where the distinction between classes is less clear (e.g., items 5, 8).

The capability to express uncertainty allows for a more complex interpretation of the results which is a valuable feature. In a real-world application, the overall effectiveness of well-being assessment and intervention strategies could be improved by flagging predictions with low certainty for further investigation or monitoring.

## 6. DISCUSSION

### *6.1 Model Performance and Implications*

The Random Forest Model performed exceptionally well with an overall accuracy of 96.17%. This demonstrates that there is potential in using machine learning techniques to assess well-being via the analysis of brain wave activities. The high accuracy of the model alongside strong performance across all evaluation metrics suggests that there are distinct neural signatures associated with different states of well-being that can be detected and classified by our model.

The strength of the model in identifying "good" well-being states with precision and recall above 98% is also particularly noteworthy. This suggests that compared to normal or suboptimal states, optimal well-being might possess a more distinct signature. From a practical standpoint, this allows for the identification of individuals who are maintaining good mental health and possibly provides insights into the neural correlates of positive well-being. This could be particularly valuable for early intervention strategies.

The capability of the model to distinguish between extreme states (good and bad) with no misclassifications is also important. This clear separation implies that there are fundamental differences in brain activity patterns between these states, which could inform our understanding of the neurological basis of well-being.

The performance of the model on new, unseen data with increased variability clearly demonstrated its potential for real-world application. The ability to provide probabilistic output rather than just hard classification allows for the identification of borderline or uncertain cases that may require closer attention.

There are several important implications to these findings:
- Objective assessment: The high accuracy of our model insinuates that a more objective measure of well-being can be provided using machine learning analysis of the EEG data compared to traditional self-reporting measures that can be subjected to various biases [13].
- Early detection: The model can also be leveraged for early detection of declining mental health due to its ability to identify optimal well-being states with high accuracy. This allows for proactive interventions before significant issues arise.
- Personalised interventions: Due to the probabilistic nature of the model's output, it can support the personalization of mental health intervention whereby strategies are tailored based on the individual's specific brain activity patterns and the certainty of the well-being classification.
- Research tool: This approach can serve as a tool for researchers to gain insights into the brain mechanisms underlying mental health and happiness.
- Continuous monitoring: There is a potential for this type of model to be used for continuous, real-time monitoring of mental states with the appropriate hardware which opens up new possibilities for adaptive interventions and self-regulation strategies.

### *6.2 Feature Importance and Neuroscientific Insights*

The feature importance analysis provided valuable insights into the comparative contribution of the different types of brain waves to the overall well-being of an individual. The alpha and beta waves, which account for 63% of the importance proved to be prominent. This aligns well with existing neuroscientific literature and suggests several interesting inferences:

Alpha Waves (34% importance): The high importance of alpha waves supports theories linking alpha activity to states of relaxed alertness and positive mood. The alpha waves are often associated with activities such as meditation and mindfulness practices [22]. The finding suggests that intervention aimed at increasing alpha wave activities such as previously mentioned could be particularly effective in improving overall well-being.

Beta Waves (29% importance): The major role of beta waves in the model's classification echoes their association with focused attention and cognitive engagement. It further supports the idea that perhaps through feelings of competence and achievement, engaged mental states contribute significantly to overall well-being. This also suggests that cognitive behavioural therapies, which often involve active cognitive engagement, might be particularly effective in improving well-being.

Theta Waves (16% importance): Although less prominent than alpha and beta, theta waves still play a significant role in the model's classifications. The moderate importance of theta waves in our model suggests that processes such as memory consolidation, emotional processing, and creativity that are often associated with this type of brain wave contribute to overall well-being, perhaps by facilitating emotional regulation and problem-solving abilities.

Delta Waves (12% importance) and Gamma Waves (9% importance): While it is less influential in the model, the inclusion of delta and gamma waves does contribute to the overall accuracy, suggesting they play a part in the full picture of brain activity related to well-being. Delta waves, which are associated with deep sleep, might reflect the importance of restorative sleep for well-being. Gamma waves, linked to high-level cognitive processing, might indicate the role of complex thought and perception in overall mental health.

These insights could guide future research into targeted interventions for improving well-being through the modulation of specific brain wave patterns. For example, neurofeedback training protocols could be developed to enhance alpha and beta wave activity in specific ratios, potentially leading to improvements in overall well-being.

*6.3 Limitations and Future Directions*

While our study demonstrates the potential of machine learning in assessing well-being through brain wave analysis, several limitations should be addressed in future research:

- Synthetic data: The use of synthetic data, while allowing for initial model development and testing, is a significant limitation. Validation with real EEG recordings is necessary to confirm the generalizability of our findings. Future studies should focus on collecting and analysing large datasets of real EEG recordings with corresponding well-being assessments.

- Temporal dynamics: Our current model does not account for the temporal dynamics of brain activity. Incorporating time series analysis could provide insights into how well-being states evolve and how transitions between states occur. This could be particularly valuable for understanding the progression of mental health conditions and the effects of interventions over time.

- Individual variability: The current model does not account for individual differences in baseline brain activity patterns. Factors such as age, gender, and individual neurophysiological characteristics should be considered in future models to provide more personalised assessments [12].

- Contextual factors: While well-being is influenced by a complex interplay of biological, psychological, and environmental factors, our model focuses solely on brain wave data. Other data sources such as physiological measures (e.g., heart rate variability), environmental sensors, and self-report measures, could be integrated to enhance the model's predictive power and provide a more holistic assessment of well-being.

- Causal relationships: While associations between brain wave patterns and well-being states can be identified by the model, it does not establish causal relationships. Causal relationships linking neural activity to subjective experiences of well-being should be explored in future research [14].

- Ethical considerations: It is crucial to address privacy concerns and develop frameworks for responsible implementation as we progress towards potential real-world applications of this technology. This involves ensuring data security, obtaining informed consent, and considering the potential psychological impact of continuous mental state monitoring.

- Expanded well-being categories: As our model currently classifies well-being into three broad categories (good, normal, bad) future research could explore more nuanced classifications. This could potentially aid in identifying specific subtypes of positive and negative mental states.

- Cross-cultural validation: Well-being is a culturally influenced construct. Future studies should validate this approach across different cultural contexts to ensure its global applicability.

- Integration with intervention strategies: While our model provides a tool for assessment, future research should focus on integrating these assessments with evidence-based intervention strategies. This could lead to the development of closed-loop systems that not only detect changes in well-being but also automatically initiate appropriate interventions.

- Long-term studies: To assess the long-term reliability and predictive validity of this approach, longitudinal studies are required. This could aid in determining whether EEG-based well-being assessments can predict future mental health outcomes and respond to life events and interventions over extended periods.

*6.4 Potential Applications*

Our approach to assessing well-being through brain wave analysis could have numerous applications across various fields when validated with real-world data:

- Personal health monitoring: Individuals could be provided with real-time insights into their mental state and well-being trends over time using wearable EEG. This could empower users to make informed decisions about their lifestyle, work habits, and self-care practices to optimize their well-being.

- Clinical support: The model can be used to assist mental health professionals in objectively assessing patient well-being and tracking treatment progress. Serving as an additional tool alongside traditional diagnostic methods, it might potentially enable earlier detection of mental health issues and more personalised treatment plans.

- Workplace wellness: Anonymised, aggregated data could be used by organizations to assess and improve employee well-being while paying careful attention to ethical considerations and privacy. This could provide information that contributes to the design of work environments, policies, and support programs that promote better mental health among employees.

- Research tool: Researchers are provided with a more objective measure of well-being for use in various studies, from testing the efficacy of interventions to exploring the neurological basis of well-being [16]. This could facilitate more standardised comparisons across different studies and populations.

- Personalised mental health interventions: By providing real-time assessments of mental states, this technology could enable the development of Just-in Time Adaptive Interventions (JITAIs) for mental health, as proposed by Nahum-Shani et al. [9]. These interventions could be triggered automatically based on detected changes in brain wave patterns, offering support precisely when it's most needed.

- Neurofeedback training: Individuals to learn to modulate their brain activity patterns for improved well-being by integrating the model into neurofeedback systems. Building on the recent work by Marzbani et al. [10] on EEG-based neurofeedback for stress reduction, it potentially offers a more targeted approach based on our understanding of which brain wave patterns are most associated with positive well-being.

- Educational settings: In education contexts, students who may be struggling with stress or other mental health issues could be identified using this technology, allowing for timely support. Apart from that, it could also be used to study the neural correlates of effective learning and cognitive engagement.

- Sports and performance psychology: This technology could be utilised by athletes and performers to optimize their mental state for peak performance. It could be used to provide insights into the neural patterns associated with flow states and help in developing mental training programs.

- Meditation and mindfulness apps: The technology could also provide users with objective feedback on their practice and its effects on their brain activity and overall well-being when incorporated into meditation and mindfulness applications.

- Sleep quality assessment: With the importance of delta waves in our model, this approach could be expanded further to assess sleep quality and its impact on overall well-being with the potential of integration with existing sleep-tracking technologies.

- Virtual Reality (VR) therapy: In VR-based therapeutic interventions, real-time EEG monitoring could be used to adapt the virtual environment based on the user's current mental state, creating more effective and personalised therapeutic experiences.

- Artificial Intelligence (AI) companions: As AI companions become more sophisticated, integrating this type of well-being assessment could allow them to provide more empathetic and contextually appropriate responses and support.

While these applications hold great promise, it's crucial to approach their development and implementation with careful consideration of ethical implications, privacy concerns, and the need for robust validation with real-world data [15].

## 7. CONCLUSION

Our study demonstrates the potential of machine learning, specifically Random Forest classification, in assessing human well-being through the analysis of brain wave activities. The high accuracy achieved by our model, even with synthetic data, suggests that there are distinct neural signatures associated with different states of well-being. The prominence of alpha and beta waves in the classification process aligns with existing neuroscientific understanding of their roles in relaxation and cognitive function, providing a bridge between machine learning insights and established theories of brain function and mental health.

The model's ability to distinguish between different well-being states with high accuracy, particularly its strength in identifying optimal well-being, opens up new possibilities for objective, data-driven approaches to mental health assessment and intervention. The nature of the model which is probabilistic allows for a nuanced interpretation and could support more personalised approaches to mental health care.

Nevertheless, the results obtained must be viewed as a promising starting point rather than a definitive solution. While the use of synthetic data allows for initial model development and testing, it is necessary to further validation using real EEG recordings. To confirm the generalizability of our findings, prospective research should also emphasize the collection and analysis of large-scale, real-world EEG data with corresponding well-being assessments.

Ethical implications of these technologies which includes issues of privacy, consent, and the potential for misuse should also be given important consideration. The development of frameworks for responsible implementation in real-world settings should be in close association with technological innovation. This encompasses obtaining informed consent, ensuring data security, as well as cautiously considering the psychological impact of monitoring an individual's mental state.

Future research should not only emphasize on improving the accuracy and robustness of these models but incorporating it with existing mental health practices and interventions. This could include developing closed-loop systems that detect changes in well-being. In addition, it could also initiate appropriate interventions or create more sophisticated neurofeedback training protocols based on our understanding of the neural correlates of well-being.

The overlapping of research between neuroscience, machine learning, and well-being research represents an exciting frontier in our understanding of the human mind and our ability to foster mental health. As the techniques are continuously refined and the associated ethical considerations addressed, a future whereby technology can provide personalised, objective insights into our mental states which empowers individuals and healthcare providers to take proactive steps towards improved well-being is imminent.

In conclusion, our study exhibits a novel approach and should be seen as a first step in a longer journey towards a more comprehensive, objective, and personalised mental health assessment and intervention strategies. The promise of this technology is significant, but realizing its full potential will require continued research, ethical consideration, and interdisciplinary collaboration.

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## AUTHOR CONTRIBUTIONS

Sellappan Palaniappan: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
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## CONFLICT OF INTERESTS

No conflict of interests were disclosed.

## ETHICS STATEMENTS

No ethical issues. Synthetic data was used in the work.

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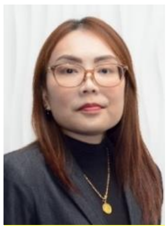
|  | **Yong Yoke Leng** is a Senior Lecturer at HELP University and an MBOT Professional Technologist. She holds a PhD in Computing from Sunway University, Malaysia. Her research focuses on computer vision, pattern recognition, data mining, and charting-based forecasting using computational finance techniques. She has published in reputable journals and presented at international conferences. Contact: yokeleng.y@help.edu.my. |