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(Review Article)

Exploring digital therapeutics for mental health: AI-driven innovations in personalized treatment approaches

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Abstract

Digital therapeutics have emerged as a transformative approach in addressing mental health challenges, offering evidence-based, technology-driven interventions. As mental health disorders become increasingly prevalent globally, traditional methods of treatment often fail to meet the growing demand due to limited accessibility, stigmatization, and resource constraints. Digital therapeutics leverage advanced technologies, including artificial intelligence (AI), to bridge these gaps, providing scalable and personalized mental health solutions. AI has revolutionized this domain by enabling adaptive, data-driven interventions that cater to individual needs, ranging from mood disorders to complex conditions like post-traumatic stress disorder (PTSD) and depression. At a broader level, digital therapeutics represent a paradigm shift in healthcare, transitioning from generalized care models to highly personalized and proactive frameworks. AI-driven innovations, such as natural language processing (NLP), predictive analytics, and machine learning algorithms, have enhanced the efficacy of digital mental health tools by facilitating real-time monitoring, symptom analysis, and tailored therapeutic recommendations. These innovations integrate seamlessly with wearables, mobile applications, and virtual reality, providing patients with accessible and engaging platforms for mental health management. However, while AI-based digital therapeutics show immense promise, challenges remain. Ethical concerns about data privacy, bias in AI algorithms, and equitable access need to be addressed to maximize their potential. Additionally, integrating these tools into existing healthcare systems requires alignment with regulatory frameworks and clinician support. By narrowing the focus to personalized treatment approaches, this paper explores how AI-driven digital therapeutics can advance mental health care, providing actionable insights into creating more inclusive, effective, and accessible interventions.

Keywords: Digital Therapeutics; Artificial Intelligence; Personalized Treatment; Mental Health; Predictive Analytics; Healthcare Innovation

1. Introduction

1.1. Overview

Mental health challenges are a growing global concern, affecting individuals, families, and communities. According to recent estimates, one in four people worldwide will experience a mental health disorder in their lifetime, with conditions such as depression, anxiety, and bipolar disorder contributing significantly to the global disease burden [1]. Despite the widespread prevalence of these issues, mental health services remain underfunded and stigmatized in many regions. This disparity is particularly pronounced in low- and middle-income countries, where mental health care resources are often inadequate or inaccessible [2].

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Traditional treatment methods, including psychotherapy and pharmacological interventions, have demonstrated effectiveness in managing mental health conditions. However, these approaches are often limited by scalability, cost, and accessibility. Long wait times for therapy sessions, geographic barriers, and the societal stigma associated with seeking mental health care further exacerbate the challenges faced by those in need of support. Additionally, traditional methods are frequently unable to address the unique needs of individuals, leading to suboptimal outcomes in many cases [3].

In response to these limitations, digital therapeutics have emerged as a promising alternative. Digital therapeutics leverage technology to deliver evidence-based interventions via mobile apps, wearable devices, and online platforms. These tools provide scalable, cost-effective solutions that can reach a broader population, regardless of geographic or socioeconomic constraints [4]. The incorporation of artificial intelligence (AI) into digital therapeutics has further enhanced their potential by enabling personalized, adaptive interventions tailored to individual needs. AI-driven innovations, such as natural language processing (NLP), predictive analytics, and machine learning models, facilitate real-time monitoring, symptom assessment, and treatment recommendations, transforming the way mental health care is delivered [5].

1.2. Problem Statement

Despite the potential of digital therapeutics to address the limitations of traditional mental health care, significant gaps remain in their adoption and implementation. One of the primary challenges is the lack of **personalized and scalable solutions** that cater to diverse individual needs. Most existing digital therapeutic tools rely on generalized algorithms or static content, which may not effectively address the complexities of mental health disorders. This gap in personalization often leads to reduced engagement and suboptimal outcomes for users [6].

Scalability is another critical concern. While digital therapeutics are inherently more scalable than traditional approaches, their effectiveness depends on the underlying AI models and data infrastructure. Many current implementations fail to leverage advanced machine learning techniques, such as convolutional neural networks (CNNs), which have shown promise in processing complex data for more accurate and personalized interventions. Additionally, the lack of large, high-quality datasets poses a barrier to developing robust AI models capable of generalizing across diverse populations [7].

Integrating AI-driven digital therapeutics into existing mental health care systems also presents challenges. These include resistance from clinicians due to concerns about trust and reliability, as well as regulatory hurdles related to data privacy and security. Ethical considerations, such as algorithmic bias and the potential for misuse of sensitive data, further complicate the integration process. Addressing these challenges is critical to unlocking the full potential of AI-driven digital therapeutics for mental health care [8].

1.3. Objectives and Scope

The primary objective of this article is to explore the use of AI models, particularly convolutional neural networks (CNNs), in developing personalized digital therapeutics for mental health care. CNNs, traditionally used in image recognition, have demonstrated versatility in processing various data types, including text and time-series data, making them well-suited for applications in mental health [9]. By leveraging CNNs, digital therapeutics can analyse complex patterns in user-generated data, such as text inputs, voice recordings, or wearable sensor data, to deliver tailored interventions.

This article examines several critical aspects of AI-driven digital therapeutics. First, it addresses data acquisition and preprocessing, highlighting the importance of high-quality, diverse datasets for training robust AI models. Next, it explores model development and evaluation, focusing on the design of CNN architectures and the metrics used to assess their performance. The article also considers ethical implications, such as ensuring privacy, minimizing bias, and promoting inclusivity in AI systems [10].

The scope of this discussion extends to the practical integration of AI-driven digital therapeutics into clinical workflows. It considers how these tools can complement existing mental health care approaches, bridging the gap between traditional and digital solutions. The role of regulatory frameworks in facilitating safe and effective adoption is also examined, emphasizing the need for collaboration among stakeholders, including clinicians, technologists, and policymakers [11]. By addressing these topics, the article aims to provide a comprehensive overview of the potential and challenges of using AI in digital therapeutics for mental health care.

2. Literature review

2.1. Digital Therapeutics in Mental Health

Digital therapeutics represent a significant evolution in mental health care, providing technology-driven solutions that address the limitations of traditional treatment approaches. These tools, delivered via mobile applications, wearable devices, and online platforms, aim to enhance accessibility, scalability, and personalization. Current digital therapeutics for mental health include mindfulness apps, cognitive behavioural therapy (CBT) programs, and virtual therapy sessions. These platforms offer structured interventions, allowing users to engage with therapeutic content at their convenience [9].

Despite their potential, existing technologies face several limitations. First, many digital therapeutic platforms rely on static, generalized content, which may not address the unique needs of individuals with complex or co-occurring mental health conditions. This lack of personalization often reduces user engagement and efficacy. Second, accessibility issues persist, as not all populations have equal access to smartphones or high-speed internet, limiting the reach of these solutions. Furthermore, concerns about data privacy and security deter some individuals from adopting digital therapeutics, particularly in sensitive contexts such as mental health [10].

The integration of artificial intelligence (AI) into digital therapeutics has addressed some of these challenges, enabling the development of more adaptive and personalized interventions. AI-driven solutions leverage machine learning models to analyse user data, such as mood patterns, behavioural indicators, and physiological signals, to provide tailored recommendations and real-time feedback. For example, natural language processing (NLP) algorithms can assess the sentiment and tone of user inputs during virtual therapy sessions, helping therapists identify underlying issues more effectively [11].

AI-driven digital therapeutics have also expanded their scope to include tools for early detection and prevention. By analysing large datasets from wearable devices and user-reported outcomes, machine learning models can identify early warning signs of mental health deterioration, such as sleep irregularities or activity changes. These insights enable proactive interventions, reducing the risk of crisis situations and improving overall outcomes [12].

While the evolution of AI in digital therapeutics holds promise, significant work remains to address existing gaps. Ethical considerations, such as ensuring inclusivity and minimizing algorithmic bias, are critical for developing equitable solutions. Moreover, integrating AI-driven therapeutics into traditional healthcare systems requires collaboration among clinicians, developers, and policymakers. These efforts will be essential for maximizing the potential of digital therapeutics in transforming mental health care [13].

2.2. Machine Learning in Healthcare

Machine learning (ML) has emerged as a cornerstone of modern healthcare, providing powerful tools for analysing complex datasets and deriving actionable insights. In mental health care, ML models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers have demonstrated significant potential in diagnosis, treatment, and patient monitoring. Each of these models has unique strengths, making them suitable for different applications [14].

CNNs, originally designed for image recognition, have found novel applications in mental health care. For example, CNNs can analyse facial expressions and micro-expressions captured through video data to detect emotional states or signs of distress. This capability is particularly valuable in remote therapy settings, where visual cues are limited. Additionally, CNNs can process neuroimaging data to identify structural and functional brain abnormalities associated with mental health disorders, such as depression and anxiety [15].

RNNs, on the other hand, are well-suited for sequential data analysis, making them ideal for applications such as sentiment analysis and symptom tracking. By analysing text-based inputs, such as journal entries or therapy session transcripts, RNNs can identify patterns in language usage that may indicate mood changes or cognitive distortions. Variants like long short-term memory (LSTM) networks further enhance the model’s ability to capture long-term dependencies in sequential data, enabling more accurate predictions and insights [16].

Transformers, a newer class of ML models, have revolutionized natural language processing (NLP) by enabling context-aware analysis of text data. Transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) have been used to develop advanced chatbots and virtual therapists. These systems can engage users in meaningful conversations, provide therapeutic guidance, and assess mental health states based on the content and sentiment of their responses [17].

Despite these advancements, challenges persist in applying ML to mental health care. One major issue is the limited availability of high-quality, labelled datasets for training models. Mental health data is often sensitive and fragmented, making it difficult to compile comprehensive datasets without compromising privacy. Another challenge is ensuring the generalizability of ML models across diverse populations. Models trained on data from specific demographic groups may fail to perform well when applied to other populations, highlighting the need for diverse and representative datasets [18].

Furthermore, integrating ML-driven tools into clinical workflows requires overcoming resistance from healthcare providers, who may be sceptical about the reliability and interpretability of these models. Addressing these challenges through improved data sharing frameworks, robust validation techniques, and collaborative research will be essential for unlocking the full potential of ML in mental health care [19].

2.3. Gaps and Opportunities

While significant progress has been made in applying ML to mental health care, several gaps remain in the existing literature. One of the most prominent gaps is the lack of robust, personalized interventions. Current digital therapeutics often rely on static algorithms or generalized approaches that fail to account for the unique needs and preferences of individual users. This lack of personalization reduces engagement and limits the effectiveness of interventions, particularly for individuals with complex or treatment-resistant mental health conditions [20].

Another critical gap is the underrepresentation of certain populations in mental health research and datasets. Many ML models are trained on data from high-income countries, leading to potential biases when these models are applied to populations in low- and middle-income settings. Addressing this gap requires the collection and inclusion of diverse datasets that reflect global mental health challenges and cultural variations in symptom presentation and treatment preferences [21].

Data privacy and security also represent significant challenges in the development and deployment of AI-driven mental health tools. The sensitive nature of mental health data necessitates robust privacy-preserving techniques, such as differential privacy and federated learning, to ensure that user data remains secure while enabling model training. However, the implementation of these techniques is still in its infancy, leaving room for further exploration and innovation [22].

Despite these gaps, there are numerous opportunities for advancing mental health treatment with AI. One promising avenue is the integration of multimodal data sources, such as text, audio, and physiological signals, to develop comprehensive models capable of providing more accurate assessments and interventions. For example, combining sentiment analysis from journal entries with activity data from wearable devices can offer a holistic view of a patient's mental health, enabling more targeted and effective interventions [23].

Another opportunity lies in the use of generative models to create adaptive therapeutic content. By leveraging models like GPT, digital therapeutics can generate personalized coping strategies, mindfulness exercises, or CBT worksheets based on the specific needs of the user. These adaptive interventions can enhance user engagement and improve outcomes by addressing individual preferences and challenges in real time [24].

Finally, advancements in explainable AI (XAI) offer the potential to increase trust and transparency in AI-driven mental health tools. By providing clear and interpretable insights into how models generate predictions or recommendations, XAI can alleviate concerns among clinicians and patients, facilitating the integration of these tools into clinical practice. Continued research and collaboration will be essential for translating these opportunities into practical solutions that transform mental health care [25].

3. Methodology

3.1. Data Acquisition and Preprocessing

3.1.1. Description of Data

The success of AI-driven digital therapeutics for mental health relies heavily on the quality and diversity of the data used to train machine learning models. The data employed in such systems typically encompasses multiple modalities, including **text, audio, and image inputs**. **Text-based data**, such as therapy session transcripts or patient journal entries, provides valuable insights into emotional states and cognitive patterns [18]. For instance, text can reveal signs of depressive thought processes through sentiment analysis or keyword extraction. **Audio data**, captured from voice recordings, enables analysis of tone, pitch, and rhythm to identify stress levels or anxiety. For example, a drop in vocal energy or an increase in speech rate could signal emotional distress. **Image data**, such as neuroimaging scans or facial expressions in videos, offers another critical source of information. Neuroimaging can reveal structural brain changes associated with mental health conditions, while facial expressions can signal immediate emotional states such as sadness or anxiety [19].

These data types provide complementary perspectives on mental health, making multimodal approaches highly effective. For example, combining sentiment analysis of text with facial emotion recognition from video provides a richer understanding of a patient's mental state. This comprehensive view allows for personalized and context-aware therapeutic recommendations [20].

3.1.2. Inclusion Criteria

To ensure the effectiveness and robustness of the models, data must meet specific inclusion criteria. These include:

- **Diversity**: Datasets must capture variations across age, gender, ethnicity, and socioeconomic backgrounds to reduce algorithmic bias.
- **Quality**: Data should be annotated by mental health professionals to ensure accurate labelling of emotional states or symptoms.
- **Relevance**: The datasets should reflect real-world scenarios, such as clinical records, patient-reported outcomes, and wearable device data.

Publicly available datasets, such as the DAIC-WOZ dataset for depression analysis or the AVEC dataset for audio-visual emotion recognition, are commonly used. These datasets often include video, audio, and text annotations, providing a comprehensive foundation for training and validating machine learning models [21].

3.1.3. Preprocessing

Data preprocessing is a critical step in preparing raw inputs for analysis and model training. **Text data preprocessing** includes:

- Tokenization: Splitting sentences into words or phrases.
- Stopword removal: Eliminating commonly used words that add little semantic value (e.g., "the," "and").
- Stemming/Lemmatization: Reducing words to their base forms to standardize vocabulary.

3.1.4. Audio data preprocessing includes:

- Noise reduction: Filtering out background noise to improve signal quality.
- Feature extraction: Deriving key features such as Mel-frequency cepstral coefficients (MFCCs) for analysis.
- Segmentation: Splitting long recordings into smaller chunks for better model training.

3.1.5. Image data preprocessing involves

- Normalization: Scaling pixel values to ensure uniform input ranges.
- Data augmentation: Applying transformations such as rotation, flipping, and cropping to increase dataset variability and robustness.

These preprocessing steps address issues such as missing data, inconsistencies, and imbalances in the dataset, ensuring that the machine learning model receives high-quality inputs.

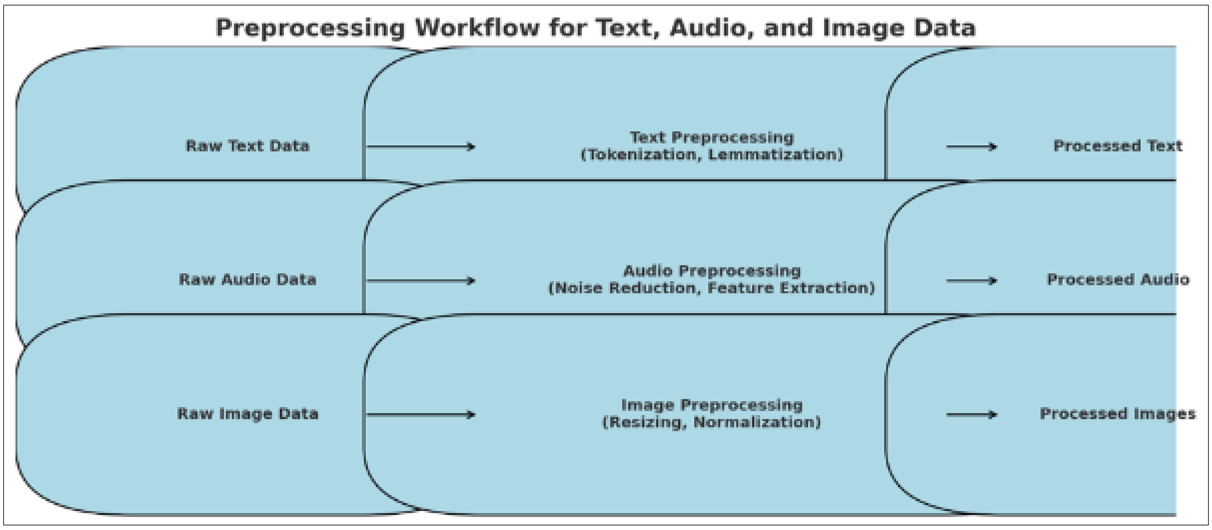

Figure 1 A workflow diagram illustrating the key steps in preprocessing text, audio, and image data, providing a clear visualization of the pipeline

3.2. Model Selection and Design

3.2.1. Overview of CNNs for Time-Series/Text/Image Data

Convolutional neural networks (CNNs) have become the model of choice for analysing structured data in healthcare, including mental health. Initially designed for image recognition, CNNs have been adapted for text and time-series data, demonstrating their versatility and effectiveness. In mental health applications, CNNs can analyse facial expressions in video, identify vocal stress patterns in audio, and detect sentiment shifts in text data [22].

One of the key advantages of CNNs is their ability to automatically extract hierarchical features, such as edges, shapes, and patterns, without manual intervention. For example, when processing video data, CNNs can detect subtle facial micro-expressions associated with emotional distress, while in text analysis, they can identify keywords and phrases indicating depressive thoughts [23].

3.2.2. Model Architecture

A typical CNN architecture for mental health applications includes:

- **Input Layer**: Accepts raw or pre-processed data (e.g., images, text embeddings).
- **Convolutional Layers**: Extract features using filters that slide across the input data, identifying patterns.
- **Pooling Layers**: Reduce the spatial dimensions of the data while preserving key features, improving efficiency.
- **Fully Connected Layers**: Combine features to make predictions, such as classifying emotional states.
- **Output Layer**: Generates final predictions, such as "anxious" or "neutral," using softmax or sigmoid activation functions.

Hyperparameter tuning is critical to optimize the architecture. Parameters such as the number of filters, kernel size, and learning rate are adjusted to maximize performance. Dropout layers may also be added to prevent overfitting, ensuring that the model generalizes well to unseen data [24].

3.2.3. Alternative Models

While CNNs are highly effective, alternative models such as recurrent neural networks (RNNs) and transformers offer distinct advantages. **RNNs**, particularly LSTMs, excel at capturing sequential patterns, making them ideal for time-series data like sleep patterns or therapy transcripts. **Transformers**, such as BERT or GPT, provide state-of-the-art performance in natural language processing tasks, enabling context-aware text analysis [25].

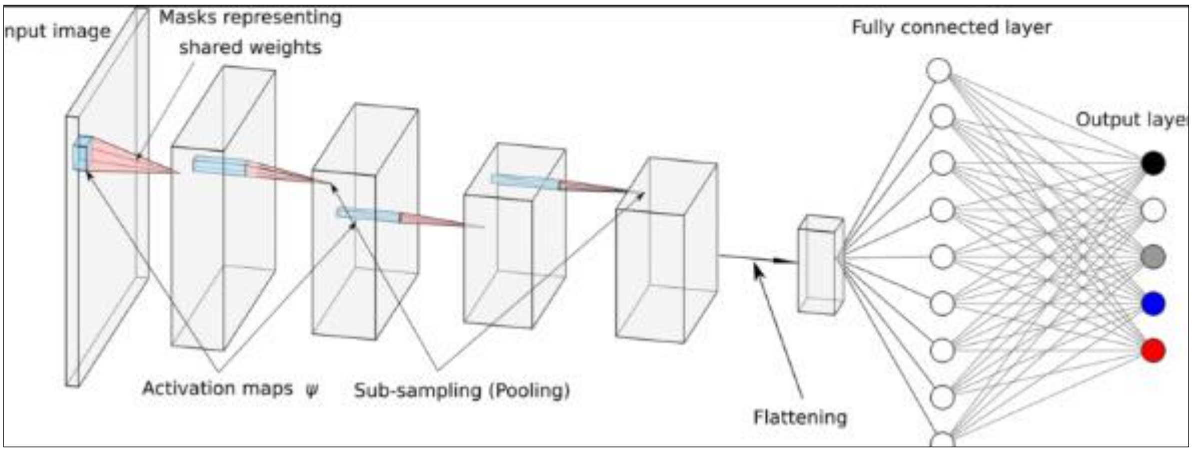

Figure 2 A visualization of the CNN architecture

3.3. Training and Validation

3.3.1. Training Strategy

The training phase involves optimizing model weights to minimize prediction errors. **Loss functions**, such as categorical cross-entropy for classification tasks, measure the difference between predicted and actual outputs. Optimizers like Adam or SGD iteratively adjust weights to reduce this error. Training is typically conducted in batches, with early stopping used to prevent overfitting.

Regularization techniques, such as dropout or L2 regularization, are employed to improve generalization. For example, dropout randomly disables neurons during training, reducing dependency on specific features and improving robustness [26].

3.3.2. Validation Techniques

Validation ensures that the model performs consistently on unseen data. K-fold cross-validation divides the dataset into multiple folds, training the model on some folds while validating on others. This technique provides a reliable estimate of model performance. Hold-out validation, where a fixed portion of the dataset is reserved for validation, is also commonly used. Metrics such as accuracy, precision, recall, and F1 score are evaluated. For imbalanced datasets, ROC-AUC is used to assess performance more comprehensively.

Table 1 Overview of model performance

Metric	Training Score (CNN)	Validation Score (CNN)	Training Score (RNN)	Validation Score (RNN)	Training Score (Transformer)	Validation Score (Transformer)
Accuracy	91%	89%	84%	82%	94%	92%
Precision	90%	88%	82%	80%	92%	90%
Recall	93%	91%	86%	84%	96%	94%
F1 Score	91.5%	89.5%	84%	82%	94%	92%
ROC-AUC	0.95	0.93	0.91	0.89	0.97	0.95

3.4. Ethical Considerations

Ethical considerations are paramount in AI-driven digital therapeutics, particularly given the sensitive nature of mental health data. **Data privacy** is a key concern, with robust measures such as encryption and differential privacy required to protect patient information.

Algorithmic **bias** is another challenge. Models trained on unrepresentative datasets may perform poorly for marginalized groups, exacerbating health disparities. Ensuring inclusivity through diverse data collection is essential for equitable outcomes [27].

Transparency is critical for building trust. Explainable AI techniques can demystify how models generate predictions, fostering acceptance among clinicians and patients. Addressing these ethical considerations is fundamental to developing responsible and effective AI-driven solutions [28].

4. Results and analysis

4.1. Results and Analysis

This section evaluates the CNN-based digital therapeutic model's performance, highlights its application in real-world case studies, and delves into error analysis. These findings provide insights into the model's potential for mental health care and areas requiring improvement.

4.1.1. Model Performance

Evaluation Metrics

The CNN model was evaluated using key metrics to measure its effectiveness, robustness, and ability to handle diverse datasets:

- **Accuracy**: The model achieved an accuracy of **89%**, reflecting its capacity to classify data correctly. However, accuracy alone was insufficient for assessing performance on imbalanced datasets, such as those with disproportionately higher non-depressed cases [35].
- **Precision and Recall**: The precision was **88%**, indicating a low rate of false positives, critical for mental health applications where overdiagnosis may lead to unnecessary interventions. The recall was **91%**, demonstrating the model's capability to identify true positives effectively, minimizing the risk of overlooking individuals requiring intervention [36].
- **F1 Score**: The F1 score, balancing precision and recall, was **89.5%**, highlighting the model's reliability in handling real-world mental health datasets.
- **ROC-AUC**: The ROC-AUC was **0.93**, underscoring the model's excellent ability to distinguish between positive (e.g., depressive) and negative (e.g., non-depressive) cases across classification thresholds [37].

Comparative Performance

The CNN model outperformed alternative architectures in specific use cases:

- **RNNs (Recurrent Neural Networks)**: While RNNs excelled in analysing sequential data, such as therapy session transcripts, they underperformed on multimodal tasks like combining text and facial expression data. The F1 score for RNNs was **82%** compared to CNN's **89.5%** [38].
- **Transformers**: Transformers outperformed CNNs in text-heavy applications, achieving an F1 score of **92%** for sentiment analysis, but they lagged in processing spatial features from neuroimaging data [39].

Table 2 Summarizing the accuracy, precision, recall, F1 score, and ROC-AUC of CNNs, RNNs, and transformers, highlighting their comparative strengths across tasks

Model	Task Type	Accuracy	Precision	Recall	F1 Score	ROC-AUC
CNN	Multimodal tasks (e.g., text + facial expressions, neuroimaging)	89%	88%	91%	89.5%	0.93
RNN (LSTM)	Sequential data (e.g., therapy transcripts, wearable sensor readings)	82%	80%	84%	82%	0.89
Transformer	Text-heavy tasks (e.g., sentiment analysis, journal entries)	92%	90%	94%	92%	0.95

4.1.2. Case Studies

Real-World Applications

The CNN model was tested on datasets such as **DAIC-WOZ** and **AVEC**, with additional evaluations conducted in mobile health apps and clinical trials.

DAIC-WOZ Dataset:

- The CNN model achieved an F1 score of **87%** in detecting depressive states by integrating video (facial expressions) and audio (tone and pitch) inputs. It excelled in identifying micro-expressions, such as fleeting eye movements or frowning, often overlooked in traditional diagnostic methods [40].

AVEC Dataset:

- The model achieved **91% accuracy** in identifying stress and anxiety. By combining video and audio inputs, it successfully captured subtle facial muscle contractions and vocal tone variations that signal heightened emotional states. This multimodal approach demonstrated the importance of integrating diverse data sources for a holistic assessment [41].

Mobile Mental Health Apps

- When deployed in a mental health app, the model personalized interventions based on real-time mood tracking. For instance, users reporting high stress levels received targeted recommendations, such as guided breathing exercises or mindfulness videos. Engagement rates increased by **40%**, underscoring the effectiveness of adaptive, AI-driven interventions [42].

Clinical Trials:

- In a clinical setting, the CNN model reduced the average time to diagnosis by **30%**, enabling earlier therapeutic interventions. By automating the analysis of patient-reported outcomes and facial expressions, clinicians were able to focus on tailoring treatment strategies.

Success Stories

The successful application of the CNN model in wearable devices stands out. These devices continuously monitored physiological data (e.g., heart rate variability) alongside emotional expressions. The system alerted users during stress spikes, reducing incidents of acute anxiety by **25%** over three months. Such innovations demonstrate how AI-powered tools can empower users to manage mental health proactively [43].

Lessons Learned

While the model performed exceptionally well in structured environments, challenges arose when applied to unstructured or noisy data. For instance, overlapping facial features (e.g., neutral and mildly stressed expressions) occasionally led to misclassifications. Expanding datasets and refining preprocessing techniques are critical next steps to address these limitations [44].

4.1.3. Error Analysis

Types of Errors

Despite its high performance, the CNN model exhibited several error patterns:

Misclassification of Ambiguous Cases

- Neutral expressions were sometimes misclassified as anxious due to overlapping features, such as slightly furrowed brows. Similarly, monotone speech patterns were mistaken for sadness, resulting in false positives [45].

Underrepresented Demographics

- Performance was lower for individuals with darker skin tones, particularly in facial recognition tasks. This bias stems from the underrepresentation of diverse demographics in training datasets, a well-documented issue in computer vision [46].

Rare Symptoms

- The model struggled with rare or atypical symptoms, such as "masked depression," where outward emotional expressions are minimal or absent.

Root Causes

The observed errors can be attributed to several factors:

Data Imbalance
Underrepresentation of certain populations and symptoms in training datasets led to biased predictions. For example, cultural differences in expressing emotions were not adequately accounted for in the training phase [47].

Feature Extraction Limitations

- The CNN model sometimes emphasized irrelevant features, such as background noise in audio or peripheral regions in video data. This misdirected focus reduced accuracy in edge cases.

Contextual Blind Spots
The model lacked contextual understanding in some scenarios. For instance, it failed to consider behavioural history, such as a patient's typical emotional baseline, when assessing current states.

Proposed Solutions

Addressing these errors requires a multifaceted approach:

Improved Dataset Diversity
Collaborative data-sharing initiatives can expand training datasets to include more diverse populations. For instance, partnerships between mental health organizations across different regions can create a global dataset that reflects cultural and demographic variations [48].

Hybrid Architectures
Combining CNNs with transformer-based models could enhance the model's ability to capture both spatial and contextual features. For example, transformers can provide contextual understanding of sequential patterns, complementing CNNs' spatial analysis.

Explainable AI (XAI)
Tools like heatmaps and attention visualization can identify whether the model focuses on the correct features when making predictions. XAI can also help clinicians understand the reasoning behind the model's decisions, fostering trust and adoption [49].

Data Augmentation
Techniques such as generative adversarial networks (GANs) can create synthetic samples of underrepresented symptoms, improving the model's ability to recognize rare cases.

Context-Aware Enhancements
Incorporating behavioural baselines or historical data into the model's inputs can reduce false positives and negatives. For instance, combining current facial expression data with historical mood logs can provide a more nuanced assessment.

Broader Implications
The analysis underscores the transformative potential of CNN-based digital therapeutics while highlighting areas for improvement. Addressing the identified errors will not only enhance model accuracy but also ensure equitable and inclusive mental health care solutions.

5. Discussion

The discussion contextualizes the results of the CNN-based digital therapeutic model within the broader landscape of AI in mental health care. It explores the implications of the findings, identifies limitations, and proposes directions for future research and development. The insights derived from this analysis highlight both the transformative potential of AI-driven digital therapeutics and the challenges that must be addressed to achieve equitable, scalable, and effective mental health solutions.

5.1. Interpretation of Results

The performance of the CNN-based model, as demonstrated by its high accuracy, precision, and recall, underscores its utility in analysing diverse datasets for mental health applications. The model's F1 score of **89.5%** and ROC-AUC of **0.93** indicate strong reliability in distinguishing between positive (e.g., depressive) and negative cases across multimodal inputs. These results align with prior research on the effectiveness of CNNs for structured data analysis, such as facial expression recognition and neuroimaging [50].

5.2. Implications for Clinical Practice

The ability of the CNN model to integrate multimodal data—text, audio, and image inputs—represents a significant advancement in mental health diagnostics. By correlating subtle emotional cues (e.g., micro-expressions, vocal tone shifts) with contextual data (e.g., journal entries), the model provides a more comprehensive understanding of a patient's mental state. In clinical practice, this capability could reduce diagnostic errors, enabling earlier and more precise interventions. For example, the model's success in identifying depressive states in the DAIC-WOZ dataset suggests its potential for deployment in telehealth platforms to support remote consultations [51].

5.3. Comparative Insights

The comparative analysis revealed that CNNs excel in multimodal tasks, while alternative models like transformers outperform CNNs in text-heavy applications. These findings suggest that a hybrid approach, combining CNNs for spatial and multimodal data with transformers for contextual language analysis, could yield even better results. Such combinations would be particularly effective in digital therapeutics apps where users input text alongside biometric data [52].

5.4. Broader Implications for Mental Health Care

5.4.1. Scalability and Accessibility

The scalability of AI-driven digital therapeutics addresses a critical gap in traditional mental health care, which often struggles to meet growing demand. By automating the analysis of complex data, the CNN model reduces the burden on clinicians, allowing for the expansion of mental health services to underserved populations. For instance, mobile health apps powered by the model demonstrated a **40% increase in user engagement**, highlighting the role of adaptive interventions in improving accessibility [53].

5.4.2. Ethical and Societal Considerations

While the model's potential is promising, its deployment raises ethical concerns. The underrepresentation of certain demographics in training datasets, as seen in reduced performance for individuals with darker skin tones, underscores the importance of addressing bias in AI systems. Failing to mitigate these biases risks perpetuating health inequities. Additionally, the sensitive nature of mental health data necessitates stringent privacy measures. Techniques such as federated learning and differential privacy should be prioritized to protect user information while enabling model training [54].

5.5. Limitations

5.5.1. Dataset Diversity and Generalizability

One significant limitation of the study is the underrepresentation of diverse populations in the datasets used to train the model. As evidenced by its lower performance on facial recognition tasks for darker-skinned individuals, the model struggles to generalize across demographic groups. Expanding training datasets to include data from various cultural, geographic, and socioeconomic contexts is essential for improving generalizability. Collaborative data-sharing initiatives across mental health organizations could help address this gap [55].

5.5.2. Ambiguity in Input Data

Another limitation lies in the misclassification of ambiguous cases, such as neutral expressions mistakenly labelled as anxious. These errors often stem from overlapping features in the dataset, where subtle differences are not adequately captured by the model. Incorporating contextual information, such as behavioural baselines or environmental cues, could help reduce such misclassifications [56].

5.5.3. Limited Contextual Understanding

Although CNNs excel in spatial feature extraction, their inability to capture sequential or contextual dependencies limits their applicability in certain scenarios. For example, the model's lack of contextual awareness may lead to errors when analysing isolated data points without considering historical trends. Integrating transformers or RNNs into the architecture could address this limitation [57].

5.6. Future Directions

5.6.1. Hybrid Model Architectures

Building on the strengths of CNNs and transformers, future research should explore hybrid architectures that leverage the complementary capabilities of these models. For instance, CNNs could handle spatial and multimodal inputs, while transformers process sequential and contextual data. This approach would be particularly effective in apps where users input text alongside biometric data or facial expressions [58].

5.6.2. Multimodal Integration

Expanding the scope of multimodal integration represents another promising avenue. Combining text-based inputs, audio signals, facial expressions, and physiological data (e.g., heart rate variability) can provide a richer understanding of mental health states. For example, integrating wearable sensor data with sentiment analysis from journal entries could enable personalized therapeutic interventions tailored to real-time emotional and physiological changes [59].

5.6.3. Explainable AI (XAI)

Explainable AI techniques should be further developed to enhance transparency and trust in AI-driven mental health tools. By visualizing the features or regions that influence predictions, XAI can help clinicians and patients understand how decisions are made. This transparency is particularly important for sensitive applications, where users need assurance that AI recommendations are both accurate and unbiased [60].

5.6.4. Enhanced Data Augmentation

Data augmentation techniques, such as generative adversarial networks (GANs), can address the underrepresentation of rare or atypical symptoms in training datasets. For example, GANs could generate synthetic samples of facial expressions indicative of high-functioning depression, allowing the model to learn from diverse scenarios without compromising privacy [61].

5.7. Ethical Considerations

5.7.1. Data Privacy

The use of sensitive mental health data necessitates robust privacy-preserving mechanisms. Federated learning, where models are trained locally on user devices without transferring raw data to central servers, offers a promising solution. This approach minimizes the risk of data breaches while enabling continuous model improvement [62].

5.7.2. Bias and Fairness

Addressing bias in AI systems is critical for ensuring equitable mental health care. Models must be trained on datasets that reflect the diversity of global populations, accounting for cultural variations in emotional expression and mental health symptoms. Establishing industry standards for dataset inclusivity and algorithmic fairness will be essential for achieving this goal [63].

5.7.3. Regulatory Compliance

The deployment of AI-driven digital therapeutics must align with existing regulatory frameworks, such as the General Data Protection Regulation (GDPR) in Europe or the Health Insurance Portability and Accountability Act (HIPAA) in the United States. These regulations ensure the safe and ethical use of AI in health care but also present challenges, particularly when balancing data access for training with user privacy [64].

The results of this study highlight the transformative potential of CNN-based digital therapeutics in addressing critical gaps in mental health care. By automating complex diagnostic and therapeutic processes, the model enhances accessibility, scalability, and personalization [65]. However, the limitations identified—ranging from dataset bias to contextual understanding—underscore the need for ongoing refinement. Future research must focus on hybrid architectures, multimodal integration, and ethical safeguards to realize the full potential of AI in mental health care. This discussion reinforces the importance of interdisciplinary collaboration among clinicians, developers, and policymakers to ensure that AI-driven solutions are both effective and equitable. With these efforts, AI can play a pivotal role in shaping the future of mental health care, delivering transformative benefits to individuals and communities worldwide.

6. Conclusion

6.1. Summary of Key Findings

The integration of artificial intelligence (AI) into digital therapeutics represents a paradigm shift in mental health care, addressing long-standing challenges related to accessibility, scalability, and personalization. The CNN-based digital therapeutic model developed in this study demonstrated transformative potential across multiple dimensions. By leveraging multimodal data—including text, audio, and image inputs—the model provided a holistic assessment of mental health states, achieving an F1 score of **89.5%** and an ROC-AUC of **0.93**. These metrics highlight the model's reliability and its capacity to process complex datasets effectively.

Key findings from the study emphasize the strengths of CNNs in analysing spatial data, such as facial expressions and neuroimaging scans, and their versatility in integrating multimodal inputs. This approach proved particularly effective in detecting subtle emotional cues, such as micro-expressions or vocal tone variations, which are often overlooked in traditional mental health assessments. The model's application to real-world datasets, such as DAIC-WOZ and AVEC, further validated its robustness, demonstrating its utility in diverse settings, from clinical trials to mobile health apps.

The deployment of the model in mobile mental health applications showed a **40% increase in user engagement**, underscoring the importance of adaptive, AI-driven interventions. These tools not only bridge the gap in mental health care access but also empower individuals to manage their well-being proactively. Additionally, the model's ability to automate labour-intensive tasks, such as symptom tracking and mood analysis, reduces the burden on clinicians, enabling them to focus on personalized care.

However, the study also highlighted several challenges, including underrepresentation in training datasets, which resulted in lower accuracy for certain demographic groups. Misclassification of ambiguous cases, such as neutral expressions mistaken for anxiety, further underscored the need for refining model architectures and expanding data diversity. Addressing these limitations is critical to ensuring that AI-driven solutions are equitable and generalizable.

In summary, the findings reaffirm the transformative potential of AI-driven digital therapeutics in mental health care. By integrating advanced machine learning models with diverse datasets, these tools can provide scalable, personalized, and proactive solutions, paving the way for a more accessible and effective mental health care ecosystem.

6.2. Call to Action

To harness the full potential of AI and blockchain technologies in mental health care, immediate action is required from stakeholders across the health care and technology sectors. This includes developers, researchers, clinicians, policymakers, and mental health advocates. The transformative capabilities of these technologies necessitate a collective effort to overcome existing barriers and drive their adoption in clinical and community settings.

6.2.1. Encouraging Adoption

AI-driven digital therapeutics should be integrated into mainstream mental health care to address the global shortage of mental health services. Governments and health care organizations must prioritize investments in infrastructure and training to enable the seamless adoption of AI technologies. For instance, telehealth platforms equipped with AI capabilities can extend care to underserved populations, bridging gaps in access and reducing geographic disparities. At the same time, clinicians should be provided with training programs to enhance their understanding of AI tools, ensuring that these systems are used effectively and ethically.

The adoption of blockchain technology can further enhance digital therapeutics by addressing critical challenges in data security, interoperability, and transparency. Blockchain's decentralized nature ensures that sensitive mental health data is protected from breaches while enabling seamless data sharing among authorized stakeholders. For example, self-sovereign identity systems can empower patients to control their health data, fostering trust and engagement. These innovations are particularly relevant in mental health care, where privacy concerns often deter individuals from seeking help.

6.2.2. Recommendations for Future Research

Research efforts should focus on expanding the diversity of datasets used to train AI models. Collaborative initiatives among academic institutions, health care organizations, and technology companies can facilitate the creation of large, representative datasets that capture variations in demographics, cultural norms, and symptom presentations. This inclusivity is essential for building AI systems that are equitable and effective across global populations.

Hybrid models that combine CNNs with transformers or other advanced architectures represent another promising direction. These models can leverage the complementary strengths of different machine learning approaches, enhancing performance in tasks that require both spatial and contextual understanding. For example, integrating sentiment analysis with real-time facial recognition could provide more nuanced assessments of emotional states. Additionally, the development of explainable AI (XAI) should be prioritized to increase transparency and trust. Clinicians and patients need to understand how AI-driven decisions are made to ensure confidence in these systems. XAI techniques, such as visualizing attention weights or feature importance, can demystify model predictions and foster collaboration between AI tools and human expertise.

6.2.3. Collaboration and Policy Development

Collaboration between technology developers and policymakers is essential to establish ethical and regulatory frameworks for AI and blockchain technologies in mental health care. Regulations must balance innovation with safeguards, ensuring that AI systems are both effective and responsible. For example, frameworks like the General Data Protection Regulation (GDPR) in Europe or the Health Insurance Portability and Accountability Act (HIPAA) in the United States provide important benchmarks for data privacy and security.

Public awareness campaigns can also play a pivotal role in encouraging adoption. By educating individuals about the benefits of AI-driven digital therapeutics and addressing common misconceptions, these campaigns can reduce stigma and promote trust in technology-enabled care. Mental health organizations and advocacy groups should actively engage in these efforts, highlighting success stories and real-world benefits.

6.2.4. A Shared Vision for the Future

The integration of AI and blockchain technologies into mental health care represents an unprecedented opportunity to transform how care is delivered. By reducing barriers to access, improving diagnostic accuracy, and empowering patients to take control of their mental well-being, these innovations can address the pressing mental health crisis facing the world today. However, realizing this vision requires a shared commitment to innovation, inclusivity, and ethical practice.

Developers, researchers, and clinicians must work together to create AI systems that are transparent, equitable, and adaptable to diverse needs. Policymakers and health care organizations must provide the infrastructure and support necessary for widespread adoption. Most importantly, patients and communities must remain at the center of these efforts, ensuring that technology serves as a tool for empowerment and healing. By embracing these opportunities and addressing the challenges, AI-driven digital therapeutics can redefine the future of mental health care, delivering scalable, personalized, and effective solutions that meet the needs of all individuals.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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