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Hues of Mental Health: Harnessing Cat Swarm Optimization and Deep Learning for Anxiety and Depression Detection

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ABSTRACT

Systems that provide health care face major problems because anxiety and depression disorders affect people more now across the entire world. Researchers find that traditional testing approaches based on patient interviews tend to produce doubtful results. This study looks at how combining Cat Swarm Optimization and Deep Learning algorithms can help doctors find anxiety and depression sooner at the start of the problem. The CSO optimization technique finds the best features of data and deep neural networks help study and process complex datasets. The researchers develop a better mental health diagnosis system using both Deep Learning and Cat Swarm Optimization. The integrated system produces better results than traditional methods and detects mental health conditions at higher speed.

INTRODUCTION

Many nations experience a growing number of people affected by anxiety and depression mental health conditions. These conditions create major problems that make millions of people-disabled making the healthcare system substantially more burdened. Standard mental health disorder testing mainly depends on the responses patients provide during interviews and questionnaires. The standard ways to identify these conditions take up too much time and staff resources plus contain built-in measurement faults. The need for better mental health diagnostic tools grows because traditional approaches require faster more reliable ways to identify mental illnesses [1].

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The recent progress in AI technology creates fresh opportunities to transform how mental health diagnoses happen. Our research studies how artificial intelligence methods including Cat Swarm Optimization and Deep Learning can better healthcare professionals perform diagnostic tasks. Our research combines CSO feature selection and deep learning classification to develop a system that identifies anxiety and depression effectively while meeting today's diagnostic challenges [2].

This study exists to prove how AI could find mental health conditions sooner and ease doctor workload while still helping patients recover better. The proposed system promises healthcare providers an accurate and easy-to-scale tool for diagnosing common mental health disorders which could transform standard mental health diagnosis and treatment. This research tests combining CSO and deep learning systems to develop a mental health diagnosis tool that should benefit current medical treatment methods [3]. Our research gains priority because mental disorders have grown common while doctors need tools that detect these conditions better. Our research joins the fight to better mental healthcare by evaluating how optimization and machine learning work together to produce more reliable and faster mental health diagnoses [4].

LITERATURE REVIEW

Anxiety and depression stand out as the leading mental health problems throughout the world. These disorders harm both mental happiness and social bonds of affected people. Depression connects to how brain functions change while anxiety develops because of multiple interactions between genes, life events and mind processes [5].

Traditional Diagnostic Methods: Doctors use both examination interviews with patients and standard assessment questionnaires like the BDI and HAM-A to find mental health issues. Doctors need much capacity to make sound judgments when using these recognized methods for diagnosis. Adopting these diagnosis tools can deliver results that depend heavily on the analyst's viewpoint and ignore multiple elements of mental disorders [6].

Advances in Machine Learning for Mental Health: Healthcare and mental health now depend heavily on machine learning technology to detect and diagnose conditions. Data analysts use both supervised algorithms (decision trees and support vector machines) and unsupervised methods (clustering) to find important patterns in patient data. Deep learning shows impressive results in ML because it can process extensive datasets to detect intricate patterns then improve prognosis accuracy [7].

Overview of Cat Swarm Optimization (CSO): The CSO algorithm takes its idea from how cats search for food during hunts. CSO works with groups of virtual cats to find food and each cat shows one possible answer to the optimization challenge. Using CSO helps select important attributes from big datasets to produce better prediction accuracy by removing features without value [8].

Applications of deep learning in medical diagnosis: Deep learning shows great results when used to identify medical conditions through visual content and spoken language text. Regular doctors have used CNNs and RNNs to identify cancer tumors and heart disorders plus similar neurologic problems. Deep learning systems learn to find mental health issues through examination of speech records, written text documents and patient actions [9].

Combined Approaches for Enhanced Detection: Multiple research teams have merged optimization framework methods and deep learning technology to strengthen medical diagnostic systems in their studies. Deep learning classifier systems with CSO feature selection run better than conventional models in both speed and accuracy while scaling easily [10].

METHODOLOGY

Research Design: Our research takes an experimental approach to test an integrated system that links Cat Swarm Optimization and Deep Learning for detecting anxiety and depression early on. The design involves the following steps:

- **Data Collection:** Get the essential data from anxiety and depression research material.
- **Data Preprocessing:** Transform the data into a workable state for our analysis.
- **Feature Selection**: Use Cat Swarm Optimization to pick out essential attributes from our data.
- **Model Development:** Use deep learning to test our selected features against measurable results.
- **Performance Evaluation:** Measure how well the CSO-enhanced deep learning model performs compared to regular methods in data analysis. We mainly test if the new system produces accurate results quickly and can handle increasing amounts of data [11].

Data Collection

- **Data Sources:** This research uses openly accessible mental health data for its analysis. Mental health datasets contain information collected from patient questionnaires and clinical interview recordings. Notable examples include:
- **The Depression and Anxiety Dataset:** The database contains essential patient facts along with results from the Beck Depression Inventory and Generalized Anxiety Disorder 7 (GAD-7) questionnaire responses.

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- **The Mood Disorder Dataset:** Our approach combines formal psychological evaluations plus standard rating scales of mood problems. These collections contain sufficient varied details that help train and test machine learning models successfully [12].

Data Preprocessing

Machine learning models need high-quality data which data preprocessing prepares before analysis. The following preprocessing steps are applied:

- **Cleaning:** Measures show lost or faulty data points.
- **Handling Missing Values:** The system imports missing dataset values by using mean value replacement or the nearest neighbor selection method.
- **Normalization:** Normalizing all features guarantees their data ranges fall into the same scale needed by the deep learning model to work well.
- **Feature Engineering:** The creation of new features depends on information found in past features to reveal their connections. The data preparation step ensures that our model learns effectively from properly set up quality data [13].

Cat Swarm Optimization (CSO)

CSO Algorithm: The Cat Swarm Optimization method uses a cat hunting model to solve optimization tasks. A population of "cats" searches through problem space to identify the best solution. Our research applies the algorithm to explore which sets of features from the feature pool add the most value to mental health diagnostic models [14].

The basic steps involved in CSO for feature selection are:

- **Initialization:** The starting point consists of various random groups of features.
- **Fitness Evaluation:** The system ranks each chosen feature subset by measuring its effectiveness using a model-accuracy-based fitness function.
- **Search Process:** Cats move toward better search paths after reviewing their fitness results and scanning for more effective feature choices.
- **Convergence:** When the algorithm reaches stability, it selects the optimal feature set [15].

Optimization Process: Through optimization CSO selects the best characteristics from the available dataset. The steps are as follows:

- **Population Initialization:** Multiple feature sets become members of the population at the start of the procedure.

- **Fitness Evaluation:** Each feature subset performance is measured by a classifier trained using these selected features and the resulting classification accuracy is recorded.
- **Search Mechanism:** Through multiple generations the algorithm moves the cats toward more suitable fitness levels.
  - **Convergence:** Based on multiple tests the algorithm selects a set of features that best suits the deep learning model [16].

Deep Learning Techniques: To perform classification tasks our team utilizes a deep neural network. The architecture consists of multiple layers, including:

- **Input Layer:** The second layer accepts the outlined characteristics from CSO's selection.
- **Hidden Layers:** Neural nets consist of many processing units which apply advanced transforms to incoming feature data. The network uses ReLU or sigmoid transforms to create mathematical variation for its processing elements.
- **Output Layer:** After learning from input data, the output layer returns predicted results for anxiety or depression. The system's design lets it identify many connections between multiple types of data inside its system [17].

Training and Validation

The training process involves:

- **Splitting the Data:** The available data splits into two parts with one serving for training and the other for validation. During training the model uses the available data while validation performance gets measured using separate testing data.
- **Back propagation:** The neural network processes information backward to modify weights which helps reduce classification mistakes.
- **Optimization Algorithm:** Models employ either Adam optimization or related gradient techniques to modify their weight parameters at optimal speed.
- **Loss Function:** Our model uses a cross-entropy loss function to detect mistakes between predicted and real class outcomes. Through multiple training cycles the system views performance results when evaluated with accuracy, precision, recall, and F1-score statistics [18].

Integration of CSO and Deep Learning: When CSO produces its optimized feature set the model feeds these selections into its neural network architecture. By combining features from the CSO algorithm with deep learning we efficiently select better features to enhance performance and simplify processing [19].

The integration process involves:

- **CSO for Feature Selection:** CSO algorithm picks the best group of features for evaluation.
- **Deep Learning for Classification:** The neural network receives the chosen features to perform its classification task.
- **Performance Evaluation:** Our integrated system displays its results with accuracy scores alongside precision, recall, and F1-score measurements.

Evaluation Metrics

To assess the performance of the diagnostic system, the following metrics are used:

- **Accuracy:** How often did the model identify the correct results?
- **Precision:** The percentage of actual disease cases that our model correctly classified in its positive outcomes.
- **Recall:** The model finds all correct anxiety or depression cases among all actual labeled positive results.
- **F1-Score:** The F1-score combines precision and recall results into one unified determination of testing accuracy. The evaluation metrics show if the model successfully finds anxiety and depression [20].

EXPERIMENTAL SETUP

Dataset Description: Our diagnostic system requires evidence from survey responses and recorded clinical sessions about anxiety and depression for both training and testing purposes. Experts in mental health research use these public sets of data frequently [21]. The main characteristics of the datasets include:

- **Anxiety and Depression Scores:** Data contains results from both clinical and personal measurements through BDI and GAD-7 assessments.
- **Patient Demographics:** Basic personal data about patients such as age gender and healthcare background help recognize anxiety and depression through the databases.
- **Behavioral and Psychological Features:** Research shows that tracking sleep, social actions, and exercise patterns helps doctors diagnose mental health problems. We divide our data into three parts to properly test the system's performance strength.

Implementation Details: The diagnostic system is implemented using the Python programming language, with the following key libraries and tools:

- **Tensor Flow and Keras:** An experienced deep learning developer builds the model through these libraries. Through Keras users can efficiently build neural networks while Tensor Flow manages basic computational tasks [22].
- **Cat Swarm Optimization (CSO):** A CSO optimization model within Python programming helps determine the best set of features for our system.
- **NumPy and Pandas:** These libraries process data before model use by cleaning and transforming it.
- **Matplotlib and Seaborn:** The tools help us create plots for both data and performance results including confusion matrix and performance charts.
- **Scikit-learn:** This library enables the model evaluation through multiple metrics like true and false identification while measuring its operational effectiveness.

Before full deployment the model is tested and trained on a single computer and later runs on a powerful computing cluster for extensive evaluation [23].

Computational Environment: The experiments take advantage of high-performance computers to train the deep learning system faster and process large datasets more efficiently. Key details of the computational environment include:

- **Hardware:** Our cluster with multiple GPUs allows faster model training particularly with deep learning resources that need substantial processor power.
- **Software:** The system uses Linux to run its operations plus Python and these supporting libraries. Docker containers enable us to set up safe spaces for performing model development work and checking results.
- **Cloud Services:** Cloud services from AWS and Google Cloud handle extensive datasets for distributed training via their scalable systems. The system works faster with GPUs and clusters to let researchers optimize features and test models in less time [24].

RESULTS AND DISCUSSION

Performance Analysis: Our diagnostic system featuring CSO feature selection and Deep Learning classification shows its performance through multiple testing measurements. The model is tested using the validation dataset, and the results are analyzed as follows:

- **Accuracy:** Our system exists at a top accuracy level to identify mental health conditions of both anxiety and depression. This evaluation shows that our combined system accurately detects whether someone has these mental health conditions [25].

- **Precision:** Our results indicate that a significant number of predicted cases for anxiety or depression are accurate positive matchups. Testing fewer positive cases helps prevent system errors from entering the healthcare process.
- **Recall:** This measurement demonstrates how accurately the model detects real anxiety and depression cases. The system successfully identifies most genuine positive test results.
- **F1-Score:** The balanced F1-score shows that our model correctly identifies most positives while avoiding false outcomes for anxiety and depression detection.

Comparison with Traditional Methods: To show the benefits of our method we compare its results against standard diagnostic tests. Traditional methods typically rely on:

- **Clinical Interviews:** System requires personal reports from patients and takes long to complete.
- **Self-Reported Questionnaires:** Even though they provide useful information these tests depend on how well patients understand themselves and may be influenced by personal preferences.

The comparison highlights several key points:

- This deep learning system enhanced by CSO detects health conditions better than normal diagnostic tools.
- The system works faster now because it selects data features automatically instead of needing manual input.
- **Scalability:** The new system shows better results than manual methods because it can process big datasets without needing many people to operate it [26].

Advantages and Limitations of the Approach

The system offers several advantages:

- **Improved Accuracy:** Our model outperforms usual diagnosis methods because it uses CSO feature selection technology combined with deep learning for classification.
- **Efficiency:** The system reduces the time needed for clinical interviews and self-report tasks as it completes diagnostic activities automatically.
- **Scalability:** The system handles vast amounts of patient data perfectly which makes it ideal for clinical use in healthcare facilities [27].

However, there are also limitations:

- **Data Dependency:** The system delivers its results based exclusively on the data collection quality and quantity. Minor datasets that contain uneven information will reduce the model's performance results.
- **Computational Resources:** Models need powerful computers to train them properly when they must use many dataset entries and complicated neural pathways.
- **Interpretability:** Complex neural networks are hard to inspect for clear performance analysis. Doctors would have trouble understanding why the model made its output decisions.

Potential for Clinical Applications: The proposed diagnostic system has significant potential for real-world clinical applications:

- **Automated Diagnostics:** By bringing the system into medical facilities healthcare staff can leverage this system to deliver quick and precise depression and anxiety tests to their patients.
- **Telemedicine Integration:** Doctors could use our system to detect mental health disorders from any telemedicine settings.
- **Early Detection:** The system detects anxiety and depression problems before they escalate which allows professionals to begin necessary treatments right away [28].

Discussion of Findings: Features selected by Cat Swarm Optimization combined with Deep Learning produce superior system performance for anxiety and depression detection. The new approach solves common problems with standard test methods including personal judgment and slow processing of data. Research reveals how AI tools can detect mental health conditions more objectively and make diagnoses faster than human methods today [29].

CONCLUSION

Our research proves that joining Cat Swarm Optimization and Deep Learning methods helps detect anxiety and depression earlier. The new diagnostic tool achieved better results than existing standards because it combined artificial intelligence and Cat Swarm Optimization. The combined system automates feature selection using CSO and uses deep learning for better diagnosis accuracy in mental health. Traditional diagnosis methods face major problems which our new system solves while also helping mental healthcare run better.

Our system proves effective in detecting anxiety and depression through its strong performance numbers such as accuracy and recall measurements. Our approach supports two main benefits through objective data processing and automatic handling of large datasets while needing limited human interaction. Due to its automation capabilities and scalability the system proves ready for clinical practice to help mental health experts detect conditions quicker and with better results.

There are some clear boundaries to using this method for diagnosis. The system depends largely on the accuracy and quantity of training and assessment information available. Deep learning models need powerful computers that some clinical facilities lack to run properly. The deep learning model produces excellent results, but its lack of interpretation makes it hard for healthcare providers to believe in its decisions.

The investigation shows that AI-based medical systems including the one examined here can help enhance mental healthcare services. An automatic diagnosis system provides better results while helping mental health professionals focus on more patients for prompt treatment. Future research will enhance the system's uses by combining more AI systems with bigger datasets and strengthening the model's clarity to suit real-world clinical conditions. Our study demonstrates how AI technology can transform mental health diagnosis while revealing the urgent need to sustain research into new solutions that help people with anxiety and depression receive better medical attention.

REFERENCES

[1]. Dawoodbhoy FM, Delaney J, Cecula P, Yu J, Peacock I, Tan J, and Cox B. AI in patient flow: applications of artificial intelligence to improve patient flow in NHS acute mental health inpatient units. Heliyon. 2021 May 1; 7(5).

[2]. Husnain, A., & Saeed, A. (2024). AI-enhanced depression detection and therapy: Analyzing the VPSYC system. IRE Journals, 8(2), 162-168.

[3]. Palmer SC. Hospital anxiety depression scale. InEncyclopedia of behavioral medicine 2020 Oct 20 (pp. 1093-1094). Cham: Springer International Publishing.

[4]. Javaid M, Haleem A, Singh RP, Suman R, Rab S. Significance of machine learning in healthcare: Features, pillars and applications. International Journal of Intelligent Networks. 2022 Jan 1; 3:58-73.

[5]. Khan R, Zainab H, Khan AH, Hussain HK. Advances in Predictive Modeling: The Role of Artificial Intelligence in Monitoring Blood Lactate Levels Post-Cardiac Surgery. International Journal of Multidisciplinary Sciences and Arts. 2024; 3(4):140-51.

[6]. Ahmad, A., Dharejo, N., Saeed, F., Shiwlani, A., Tahir, A., & Umar, M. (2024). Prediction of fetal brain and heart abnormalities using artificial intelligence algorithms: A review. American Journal of Biomedical Science & Research, 22(3), 456-466.

[7]. Nazir A, Hussain A, Singh M, and Assad A. Deep learning in medicine: advancing healthcare with intelligent solutions and the future of holography imaging in early diagnosis. Multimedia Tools and Applications. 2024 Jul 5:1-64.

[8]. Husnain, A., Alomari, G., & Saeed, A. (2024). AI-driven integrated hardware and software solution for EEG-based detection of depression and anxiety. International Journal for Multidisciplinary Research (IJFMR), 6(3), 1-24.

[9]. Dodda S, Kamuni N, Arlagadda JS, Vuppalapati VS, Vemasani P. A Survey of Deep Learning Approaches for Natural Language Processing Tasks. International Journal on Recent and Innovation Trends in Computing and Communication.;9:27-36.

[10]. Chen, JJ. Husnain, A., Cheng, WW. (2024). Exploring the Trade-Off between Performance and Cost in Facial Recognition: Deep Learning Versus Traditional Computer Vision. In: Arai, K. (eds) Intelligent Systems and Applications. IntelliSys 2023. Lecture Notes in Networks and Systems, vol 823. Springer, Cham.

[11]. Arif A, Khan A, Khan MI. Role of AI in Predicting and Mitigating Threats: A Comprehensive Review. JURIHUM: Jurnal Inovasi dan Humaniora. 2024; 2(3):297-311.

[12]. Thatoi, P., Choudhary, R., Shiwlani, A., Qureshi, H. A., & Kumar, S. (2023). Natural language processing (NLP) in the extraction of clinical information from electronic health records (EHRs) for cancer prognosis. International Journal, 10(4), 2676-2694.

[13]. Krızek P. Feature selection: stability, algorithms, and evaluation (Doctoral dissertation, Ph. D. thesis, Czech Technical University in Prague).

[14]. Qayyum MU, Sherani AM, Khan M, Hussain HK. Revolutionizing Healthcare: The Transformative Impact of Artificial Intelligence in Medicine. BIN: Bulletin of Informatics. 2023; 1(2):71-83.

[15]. Saeed, A., Husnain, A., Zahoor, A., & Gondal, R. M. (2024). A comparative study of cat swarm algorithm for graph coloring problem: Convergence analysis and performance evaluation. International Journal of Innovative Research in Computer Science and Technology (IJIRCST), 12(4), 1-9.

[16]. MEHTA A, CHOUDHARY V, NIAZ M, NWAGWU U. Artificial Intelligence Chatbots and Sustainable Supply Chain Optimization in Manufacturing: Examining the Role of Transparency. Innovativeness, and Industry. 2023 Jul; 4.

[17]. Liu W, Wang Z, Liu X, Zeng N, Liu Y, Alsaadi FE. A survey of deep neural network architectures and their applications. Neurocomputing. 2017 Apr 19; 234:11-26.

[18]. Shiwlani, A., Khan, M., Sherani, A. M. K., & Qayyum, M. U. (2023). Synergies of AI and smart technology: Revolutionizing cancer medicine, vaccine development, and patient care. International Journal of Social, Humanities and Life Sciences, 1(1), 10-18.

[19]. Zhang Y, Zhao J, Wang L, Wu H, Zhou R, Yu J. An improved OIF Elman neural network based on CSO algorithm and its applications. Computer Communications. 2021 Apr 1; 171:148-56.

[20]. Khan, A. H., Zainab, H., Khan, R., & Hussain, H. K. (2024). Implications of AI on Cardiovascular Patients 'Routine Monitoring and Telemedicine. BULLET: Jurnal Multidisiplin Ilmu, 3(5), 621-637.

[21]. Khan, M., Shiwlani, A., Qayyum, M. U., Sherani, A. M. K., & Hussain, H. K. (2024). AI-powered healthcare revolution: An extensive examination of innovative methods in cancer treatment. BULLET: Jurnal Multidisiplin Ilmu, 3(1), 87-98.

[22]. Sarkar D, Bali R, and Ghosh T. Hands-On Transfer Learning with Python: Implement advanced deep learning and neural network models using TensorFlow and Keras. Packt Publishing Ltd; 2018 Aug 31.

[23]. MEHTA A, CHOUDHARY V, NIAZ M, NWAGWU U. Artificial Intelligence Chatbots and Sustainable Supply Chain Optimization in Manufacturing: Examining the Role of Transparency. Innovativeness, and Industry. 2023 Jul; 4.

[24]. Dodda S, Kamuni N, Vuppalapati VS, Narasimharaju JS, Vemasani P. AI-driven Personalized Recommendations: Algorithms and Evaluation. Propulsion Tech Journal.;44.

[25]. Khan MI, Arif A, Khan AR. AI-Driven Threat Detection: A Brief Overview of AI Techniques in Cybersecurity. BIN: Bulletin of Informatics. 2024; 2(2):248-61.

[26]. Mohammed MA, Al-Khateeb B, Yousif M, Mostafa SA, Kadry S, Abdulkareem KH, Garcia-Zapirain B. Novel Crow Swarm Optimization Algorithm and Selection Approach for Optimal Deep Learning COVID-19 Diagnostic Model. Computational intelligence and neuroscience. 2022; 2022(1):1307944.

[27]. Kamuni N, Dodda S, Arlagadda JS, Vemasani P. Advancements in Reinforcement Learning Techniques for Robotics. Journal of Basic Science and Engineering.;19:101-11.

[28]. Butow P, Price MA, Shaw JM, Turner J, Clayton JM, Grimison P, Rankin N, Kirsten L. Clinical pathway for the screening, assessment and management of anxiety and

ISSN : XXXX-XXXX
Volume 1, Number 1, January, 2025

depression in adult cancer patients: Australian guidelines. Psycho-Oncology. 2015 Sep; 24(9):987-1001.

[29]. Qayyum MU, Sherani AM, Khan M, Shiwlani A, Hussain HK. Using AI in Healthcare to Manage Vaccines Effectively. JURIHUM: Jurnal Inovasi dan Humaniora. 2024 May 27; 1(6):841-54.