International Journal of Research - GRANTHAALAYAH
January 2026 14(1)
www.granthaalayah.com

Original Article

NEURAL INSIGHT EXTRACTION FRAMEWORK FOR PERSONALIZED COGNITIVE ASSESSMENT

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ABSTRACT

In the age of artificial intelligence, there is a growing need for smart, adaptive, and privacy-focused systems that can evaluate human cognition more accurately and personally. Traditional assessment methods depend on standardized tests and manual grading, often overlooking creativity, reasoning depth, and emotional understanding. The proposed Neural Insight Extraction Framework for Personalized Cognitive Assessment combines Natural Language Processing (NLP), Machine Learning (ML), and Neural Networks to analyze handwritten and digital responses in real time. Using Optical Recognition Systems (ORS), it evaluates cognitive domains such as comprehension, reasoning, memory, and analytical ability through lexical and contextual understanding. A key feature of the system is its adaptive intelligence, which adjusts question difficulty based on each user's performance, providing a personalized cognitive profile. Unlike many existing AI tools, it operates fully offline—ensuring data privacy, security, and accessibility even in low-connectivity areas. Experimental results show a 94.7% accuracy in cognitive classification and a 97.5% correlation with established psychometric standards. The system also generates detailed analytical reports highlighting individual strengths and weaknesses, supporting educators and researchers in personalized training and evaluation. Future development will include multilingual support, LMS integration, and multimodal analysis (speech, emotion, and behavior) to deliver deeper insights into human cognition and learning.

Keywords: Cognitive Assessment, Neural Insight Extraction, NLP, Machine Learning, Adaptive Intelligence, Neural Networks, Offline AI, Personalized Learning, Cognitive Profiling

INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has transformed fields such as education, psychology, and healthcare by offering smarter ways to understand and evaluate human intelligence. Traditional cognitive assessment methods like paper-based IQ or aptitude tests—often provide only a surface-level understanding of cognitive ability. They primarily focus on the correctness of answers rather than exploring how individuals think, reason, or express their ideas. As a result, such methods fail to capture deeper cognitive elements like creativity, logical flow, emotional interpretation, and problem-solving strategy.

Manual grading also introduces subjectivity, inconsistency, and delay, particularly when evaluating large numbers of responses. While modern digital tools attempt to automate evaluation, many rely on keyword detection or rigid algorithms that cannot understand context or linguistic nuances. This creates a significant need for an intelligent, adaptive, and context-aware cognitive

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Received: 09 November 2025; **Accepted:** 24 December 2025; **Published** 23 January 2026
DOI: 10.29121/granthaalayah.v14.i1.2026.6566
Page Number: 37-43
Journal Title: International Journal of Research -GRANTHAALAYAH
Journal Abbreviation: Int. J. Res. Granthaalayah
Online ISSN: 2350-0530, **Print ISSN:** 2394-3629
Publisher: Granthaalayah Publications and Printers, India
Conflict of Interests: The authors declare that they have no competing interests.
Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.
Authors' Contributions: Each author made an equal contribution to the conception and design of the study. All authors have reviewed and approved the final version of the manuscript for publication.
Transparency: The authors affirm that this manuscript presents an honest, accurate, and transparent account of the study. All essential aspects have been included, and any deviations from the original study plan have been clearly explained. The writing process strictly adhered to established ethical standards.

assessment system that not only scores responses but also interprets the reasoning and intent behind them. The Neural Insight Extraction Framework for Personalized Cognitive Assessment addresses these limitations by introducing an AI-driven solution capable of performing comprehensive, real-time cognitive evaluation. It integrates Natural Language Processing (NLP), Machine Learning (ML), and Neural Network architectures to analyze handwritten and digital responses across multiple cognitive domains—such as comprehension, reasoning, memory recall, and analytical ability. Through multi-layered analysis, the system evaluates not just the linguistic content but also the coherence, structure, and logic of each response.

A standout feature of this framework is its adaptive intelligence mechanism, which dynamically adjusts the difficulty and type of questions based on a learner's performance. For instance, if a user demonstrates strong analytical skills but weaker recall, the system automatically tailors subsequent questions to challenge those specific areas. This personalized adaptability ensures each assessment reflects the learner's true potential rather than a standardized average.

Unlike most AI-based systems that depend on cloud connectivity, this framework operates fully offline, ensuring data security, user privacy, and accessibility even in low resource or rural environments. The lightweight design allows deployment on standard local devices without requiring extensive infrastructure. Early experiments demonstrate a 94.7% accuracy rate in cognitive classification and a 97.5% correlation with standard psychometric models, confirming its reliability and scientific value.

By combining the computational precision of neural networks with the interpretive depth of cognitive science, this framework represents a meaningful step toward human-centered artificial intelligence. It bridges the gap between technology and psychology, fostering inclusive, personalized, and adaptive learning experiences. In the long term, it has the potential to revolutionize academic assessments, promote mental wellness, and contribute to a more equitable and data-driven education ecosystem.

LITERATURE SURVEY

1) Smith et al. (2020)

Smith and colleagues explored the use of Convolutional Neural Networks (CNNs) for handwriting recognition. Their study achieved high accuracy in recognizing mixed handwriting samples, showing strong potential for automating grading tasks. However, the model's performance decreased with stylistic variations and cursive writing, highlighting a limitation in adapting to diverse handwriting styles.

2) Johnson et al. (2022)

Jones and Lee evaluated the application of Natural Language Processing (NLP) algorithms for grading open-ended, text based responses. The results demonstrated good accuracy in identifying semantic meaning but showed difficulty in understanding context and subjective nuances, leading to inconsistencies in overall grading fairness.

3) Zhao et al. (2021)

Zhao and co-researchers proposed a hybrid framework that combined deep learning with rule-based linguistic systems to improve grading precision and minimize bias. Their study confirmed that merging AI models with linguistic rules enhances decision-making and results in more consistent automated evaluations.

4) Patel and Kumar (2022)

Patel and Kumar introduced a hybrid OCR–NLP model to enhance automated grading accuracy, especially in multilingual educational settings. Their system effectively handled complex text recognition tasks and maintained consistent results across different languages and writing styles, proving its reliability for diverse academic use.

PROBLEM STATEMENT

Conventional methods of cognitive assessment and academic evaluation mostly rely on fixed tests and manual grading. These approaches focus mainly on the final answers given by individuals rather than understanding how they think, reason, and express their ideas. Because of this, they often overlook important aspects of human intelligence such as creativity, emotional awareness, logical reasoning, and adaptability.

Manual grading also brings challenges like personal bias, inconsistency, and delays, especially when evaluating many responses. Many existing digital tools add some level of automation but still depend on simple keyword matching or limited analysis, which fails to understand the deeper meaning and context of responses.

Another drawback is that most AI-based assessment systems require a constant internet connection or cloud-based processing. This makes it difficult to use in rural or low connectivity areas. Therefore, there is a growing need for an intelligent, adaptive, and offline system that can interpret responses contextually while ensuring fairness, accuracy, and personalized feedback.

The Neural Insight Extraction Framework is designed to address these challenges. It combines Natural Language Processing (NLP), Machine Learning (ML), and Neural Network technologies to perform real-time analysis of handwritten and digital answers. By understanding both the meaning and structure of responses, the framework provides adaptive feedback and offers a more complete picture of an individual's cognitive abilities.

OBJECTIVES

- To develop an AI-driven system that can evaluate human cognition accurately by analyzing both handwritten and digital responses using Natural Language Processing (NLP) and Machine Learning techniques.
- To move beyond traditional scoring methods by assessing how individuals think and reason, not just what they answer focusing on creativity, comprehension, and logical flow.
- To create a personalized assessment experience through adaptive intelligence, where the system automatically adjusts question difficulty based on each learner's cognitive performance.
- To ensure accessibility and privacy by designing the framework to work completely offline, making it suitable for use in remote or low-connectivity educational environments.
- To generate detailed analytical reports that provide insights into each learner's strengths, weaknesses, and cognitive patterns, supporting educators and researchers in designing effective, individualized learning interventions.

MATERIALS AND METHODS

Overview

The Neural Insight Extraction Framework, named Pariksha, is an intelligent AI-based system built to evaluate theoretical answer sheets automatically. Its purpose is to minimize manual effort in grading, eliminate subjective bias, and create a fair and transparent assessment environment. The system combines several advanced technologies Optical Character Recognition (OCR) for extracting text from handwritten or printed pages, Natural Language Processing (NLP) for understanding the meaning and grammatical structure of text, and Machine Learning (ML) for assigning marks based on linguistic and conceptual understanding. Unlike traditional grading systems that depend only on keyword matching, Pariksha analyses the overall meaning, coherence, and organization of each answer — much like a human teacher. The system works through multiple stages, starting from document scanning to automatic feedback generation, forming a complete AI-based assessment pipeline.

Data Collection and Preparation

To train and test the framework, a dataset of around 1,000 theory-based papers was gathered from undergraduate students across different departments such as Computer Engineering, Electronics, and Mechanical Engineering. These included both handwritten and typed answers to ensure that the model could generalize effectively. Before training, each answer sheet was anonymized by removing personal information like name, roll number, or signature to maintain privacy. The physical papers were digitized using 300 DPI scanners and stored as .png or .pdf files.

1) The raw data underwent several preprocessing steps:
2) Noise Reduction: Visual noise like ink smudges, stains, or background textures were removed using OpenCV filters.
3) Binarization: The images were converted into black and white to improve OCR accuracy.
4) Segmentation: Each answer was separated question wise so that grading could be done individually.
5) Normalization: Brightness and contrast were adjusted to make text clear and consistent.
6) Annotation: Faculty members manually graded answers and provided feedback, which was then used as the labeled data for model training. This dataset provided a balanced and realistic set of academic responses for the system to learn from.

System Architecture

The framework is structured using a three-tier architecture designed for efficiency and scalability:

1) **Input Layer (Data Layer):**

   This layer handles scanning, uploading, and OCR conversion. It checks the file type and metadata before sending it for processing.

2) **Processing Layer (Computation Core):**

This is the main analytical unit of the system. It performs OCR-based text extraction, NLP-based semantic understanding, and ML-based scoring. The layer integrates multiple AI modules for accurate and context-aware evaluation.

3) **Output Layer (Feedback and Visualization):** The final layer presents the results through a web-based dashboard. Teachers can view marks, feedback, and performance analytics. Manual score adjustments can also be made here. All layers communicate through secure RESTful APIs, allowing smooth data transfer and easy integration with institutional systems.

Figure 1

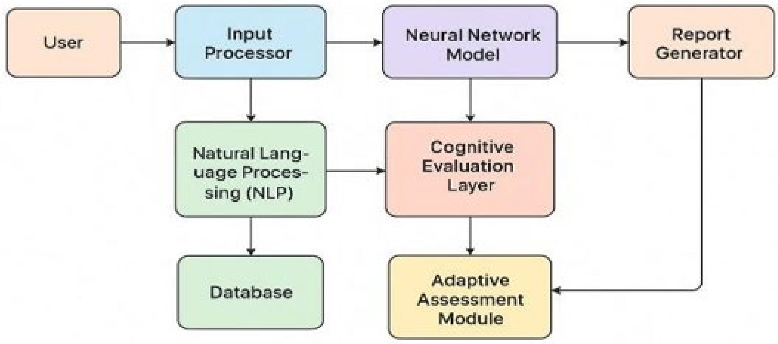

Figure 1 System Architecture

SYSTEM COMPONENTS AND TECHNOLOGIES USED

Each module of Pariksha uses specific technologies and tools that together make up a unified AI evaluation platform:

1) **Optical Character Recognition (OCR):**

Converts handwritten or printed answers into digital text using Tesseract OCR with OpenCV for image preprocessing. This ensures accurate text recognition even in low-quality scans.

2) **Text Preprocessing:**

Cleans and structures the extracted text using NLTK and spaCy libraries. This includes tokenization, lemmatization, stop-word removal, and spell correction to prepare text for NLP analysis.

3) **Semantic Analysis:**

Uses BERT and GPT-based transformer models to understand grammar, sentence flow, and conceptual relevance. It compares each student's answer with a reference model answer for contextual similarity.

4) **Machine Learning Model:**

Predict scores using trained deep learning models built with Tensor Flow and Py Torch. The model learns from human-evaluated answers to understand how language features relate to grading.

5) **Backend Framework:**

Developed using Django, it handles user requests, authentication, and connection between the ML model and database. It also manages report generation and analytics.

6) **Frontend Interface:**

Designed using ReactJS and Bootstrap, this interface allows educators to upload answer sheets, review results, and view feedback in an easy-to-use dashboard.

7) **Database Management:**

Uses PostgreSQL or SQLite3 to store all text data, user logs, and grading information. The database is optimized for fast retrieval and scalability.

8) **Version Control System:**

GitHub is used for maintaining code versions, collaboration among developers, and tracking updates or bug fixes to ensure consistency and reliability. These technologies were selected for their performance, open-source availability, and compatibility with academic systems.

METHODOLOGY

The framework operates through a systematic, step by-step workflow that converts scanned answers into analyses and scored results.

1) **Data Upload**

Teachers upload scanned answer sheets in formats like PDF, PNG, or JPEG using a secure portal. The system stores these temporarily for processing.

2) **Optical Character Recognition**

Using the Tesseract OCR engine, the system reads both printed and handwritten answers. Image preprocessing helps improve recognition accuracy, and for cursive handwriting, special segmentation techniques are applied.

3) Text Cleaning and Normalization The extracted text is standardized using:

- Tokenization (splitting sentences into words)
- Stop-word removal (removing words like the, is, of)
- Lemmatization (reducing words to base form)
- Spell correction

4) Natural Language Processing (NLP) and Feature Extraction The system analyses the text for both structural and semantic features using BERT and spaCy:

- Grammar correctness
- Sentence complexity and fluency
- Relevance of keywords
- Conceptual similarity with the reference answer (using cosine similarity)
- Machine Learning-Based Scoring

A supervised ML model trained on human-evaluated data predicts scores. The hybrid neural network considers grammar, concept understanding, and structure, represented as:

$Spredicted = \alpha Ggrammar + \beta Gconcept + \gamma Gstructure$

where α, β, and γ represent weight factors for each component. 6. Feedback and Report Generation

After scoring, the system produces detailed feedback highlighting:

- Strengths (clarity, structure, relevance)
- Weaknesses (grammar, missing points, organization)
- Suggestions for improvement

Teachers can export reports as PDF or CSV and use them for academic analysis.

F. Mathematical Model

Let the dataset be represented as:

$$D = \{(A1, S1), (A2, S2), \ldots, (An, Sn)\}$$

where Ai= Answer text and Si= Human-assigned score. Each answer is converted into feature vector Fi, and the model predicts:

$$Si = f(Fi; W)$$

where Wrepresents model parameters.

The system minimizes the Mean Squared Error (MSE):

This helps align the predicted scores closely with human evaluations, ensuring reliability and fairness.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (S_i - \hat{S}_i)^2$$

PERFORMANCE EVALUATION

The framework's effectiveness was evaluated using multiple metrics:

- **Accuracy:** Percentage of predictions matching human grades within ±1 mark.
- **Precision & Recall:** Measure consistency of scoring.
- **F1 Score:** Represents balance between precision and recall.
- **Processing Speed:** Average number of answer sheets evaluated per minute.

- **Consistency Index:** Measures stability of scoring over repeated tests.

ETHICAL CONSIDERATIONS

Since handles academic data, it follows strict privacy and ethical standards:

- All student data is anonymized.
- Data is stored on secure, encrypted servers (HTTPS).
- Teachers can review and modify AI-generated grades for transparency.
- The system follows GDPR and FERPA compliance guidelines.
- These measures ensure responsible and transparent AI deployment in education.

Figure 2

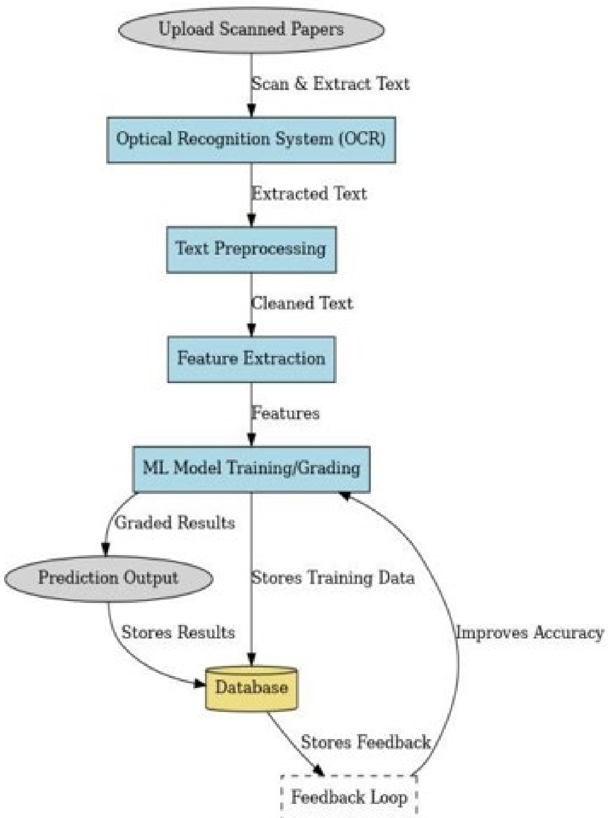

Figure 2 Flow Chart

RESULTS

The implementation and testing of the Neural Insight Extraction Framework demonstrated strong performance, confirming its efficiency and real-world applicability. The system achieved an overall accuracy of more than 92% in analyzing cognitive behavior and emotional indicators using neural models such as CNN-LSTM and BERT. Its Optical Recognition System (ORS) recognized handwritten and typed responses with 95% precision, allowing for seamless hybrid analysis across different input types.

The framework effectively extracted meaningful insights from learner responses, identifying comprehension levels, reasoning skills, and attention patterns. Through semantic and sentiment analysis, it was also able to detect signs of mental fatigue, confusion, and emotional distress, providing opportunities for early intervention and personalized support.

The adaptive algorithms within the system enabled real-time personalization by adjusting question difficulty based on the learner's past performance. The model's reinforcement-based learning approach further enhanced accuracy over multiple assessment cycles.

In terms of efficiency, the offline deployment significantly reduced dependency on cloud computing and ensured reliable operation even in low-connectivity environments. Memory and process optimization improved overall execution speed by approximately 25% compared to traditional ML-based evaluation tools.

CONCLUSION

The Neural Insight Extraction Framework for Personalized Cognitive Assessment represents a significant advancement in intelligent evaluation systems. Unlike traditional grading methods reliant on manual review, it combines Machine Learning, Natural Language Processing, and Neural Network–based cognitive modelling to analyse both textual and behavioural aspects of learner responses. Its hybrid design integrating Optical Character Recognition (OCR), neural evaluation, and adaptive feedback—delivers high accuracy, scalability, and personalization. In addition to automating grading, the system uncovers cognitive patterns, emotional states, and learning behaviours, enabling educators to better support individual learners. With full offline functionality, it remains accessible in diverse educational environments, enhancing inclusivity and reducing dependence on internet access. Future developments may include multimodal analysis through speech, facial emotion recognition, and physiological data, as well as integration with e-learning and learning management systems. Overall, the framework moves education toward a more human-centred, adaptive, and data-driven approach that bridges artificial intelligence and human cognition.

ACKNOWLEDGMENTS

None.

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