Early Detection of Cognitive Skill Impairment Using Deep Learning Models: A Comparative Analysis of CNN, RNN, GPT, LSTM and GRU

Sunita Patil[a] and Swetta Kukreja[b]
Amity School of Engineering and Technology, Amity University Maharashtra, Mumbai. Maharashtra -410206, India

Keywords: Cognitive Skill Impairment, Early Detection, Deep Learning Models, CNN, RNN, GRU, LSTM, GPT.

Abstract: Early detection of cognitive skill impairment is an important key in discovering the earliest possible intervention and management. This paper presents a comparison of five deep learning-based models: Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Generative Pretrained Transformer (GPT), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) applied on the task of cognitive skill impairment classification. The best models are discussed and compared over several key performance metrics, accuracy, F1-score, precision, recall (sensitivity), Matthews Correlation Coefficient (MCC). The results show that the RNN outperforms all other models with an accuracy of 99.2%, GRU follows closely with an accuracy of 98.7%, precision of 98.7%. The results of GPT and LSTM are almost similar with accuracies of 98.5% and 98.8% but need more resources in memory to be used: 185 MB and 180 MB, respectively. CNN did not lag as it had an accuracy is 98.5%, precision is 98.6% and combined with a memory usage of 176 MB. Overall, the RNN emerged as the most efficient model, balancing high classification accuracy with low memory consumption, and thus most suitable for real-time and resource-constrained applications. This comparative analysis sets out the strengths and trade-offs of each model, providing valuable insights for further development in this field of detecting cognitive impairment.

1 INTRODUCTION

Cognitive skills are used in various domains such as education, workforce performance, and mental health. To carry out routine tasks in daily life, cognitive skill is essential. The term "cognitive skill" describes a group of mental health abilities and functions that allow people to interpret, process, and use data. Memory, logical thinking, and problem solving are examples of cognitive skills. Many mental health disorders can lead to cognitive impairments. For example, conditions like depression, anxiety, and schizophrenia, dementia can affect cognitive functions like problem-solving abilities, memory, Communication, attention, concentration. This cognitive impairment can affect everyday activities, work performance, and overall quality of life.

Now a days Cognitive skill impairment problem become more sensitive. Detecting cognitive skill loss early allows for timely intervention and appropriate treatment. Early detection can advantage to better management and mediation schemes. Early identification can help prevent further deterioration and improve outcomes through targeted interventions. Traditional assessment methods have limitations in terms of personalization and interactivity (Sanchez, Melo, et al. , 2022). Traditional screening methods often depends on clinical evaluations and interactive evaluations, but these can be time-consuming, inconsistent and Costly. Existing methods often shortage the required correctness and specificity for early diagnosis, specifically in the initial or mild phases of cognitive decline skill.

Overall, the advantages of early identification highlight the significance of routine cognitive testing, particularly for those who are more vulnerable because of age, family history, or health issues.

[a] https://orcid.org/ 0009-0004-9828-5274
[b] https://orcid.org/0000-0003-4754-8826

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Frequent examinations and screenings can help promote proactive healthcare management and better results for individuals with cognitive skill impairments.

1.1 Motivation

The motivation behind developing cognitive skill detection methods in the context of mental health is to improve overall patient care and outcomes. By identifying and addressing cognitive skill loss, healthcare professionals can provide targeted interventions, improve treatment planning, and increase the value of life for those experiencing mental health problems. Additionally, integrating cognitive skill assessment into mental health care can contribute to a more broad and holistic recognizing of a person's well-being, promoting a more personalized and effective approach to treatment.

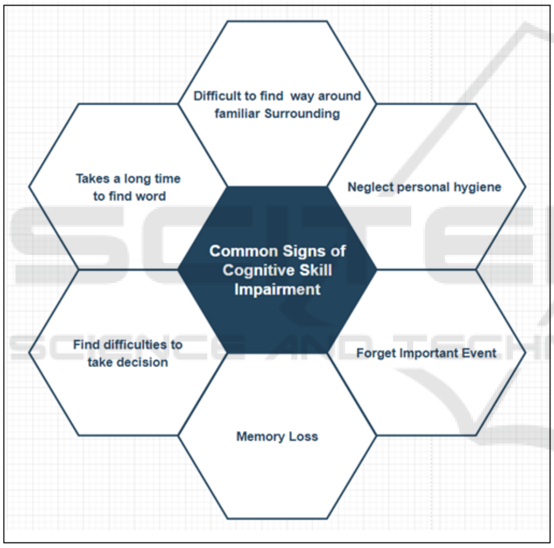

Figure 1: Common sign of Cognitive Skill Impairments

1.2 Role of Deep Learning

Recent advancement in artificial intelligence, exclusively deep learning, has proven ability for improving diagnostic accuracy and effectiveness. Deep learning utilizes multi-layered neural networks, has capabilities in identifying patterns and guessing results across several areas. In the cognitive skill impairments, deep learning models can examine complex datasets to detect small signs of early cognitive decline. Proposed research work investigates the use of modern deep learning models, particularly LSTM, GPT and GRU, RNN and CNN to analyse structured data for predicting cognitive skill impairment. The research aims to provide a comparative study of these models to assess their efficacy in early detection using a dataset with demographic and health information of Person.

1.3 Significance of the Study

The significance of utilizing deep learning for early discovery of cognitive impairments keeps in its potential to modernise diagnostic methods. By leveraging deep learning, the investigation aims to better the accuracy and relevance of cognitive impairment detects, hypothetically leading to earlier interference and healthier management of neurodegenerative diseases. Additionally, the vision grown from this research could contribute to the wider area of medical diagnostics. Moreover, integrating deep learning into cognitive assessment procedures can modernise screenings, less time-consuming, lower diagnostic costs. As these models advance and improve, they could also contribute to a deeper knowledge of the underlying tools of cognitive skill impairments, requiring insights that could initiative future research and medical treatment development.

1.4 Structure of the Paper:

The entire paper is arranged as following:

Literature Review: A review of current research on cognitive impairment detection and the purpose of deep learning in medical diagnostics.

Methodology: A complete narrative of the data sources, deep learning model architecture, and evaluation methods used in this study.

Results: Presentation and analysis of the model's performance.

Discussion: Interpretation of the results, including implications for clinical practice and future research directions.

Conclusion: Summary of findings, contributions of the study, and recommendations for implementing deep learning models in early detection of cognitive impairments.

2 RELATED WORK

2.1 Cognitive Skill Impairment: Identification and Obstacles

Cognitive function decline, extensive conditions like dementia, Alzheimer's disease, Parkinson's disease, difficulties in both identification and treatment. Existing diagnostic approaches usually utilize neuropsychological assessments, clinical assessments, and brain imaging methods. For example, the Mini-Mental State Examination and the Montreal Cognitive Assessment are commonly used tools for screening and estimating cognitive abilities (Julayanont, Phillips, et al. , 2012), (Rodriguez, Smailagic, et al. , 2010). Disadvantage of MMSE are limited assessment and Functional Impairment (Larsena, Lomholta, et al. , 2007). Brain imaging methods, like Magnetic Resonance Imaging (MRI) is key for observing brain structure. But MRI can be costly and may not detect small cognitive changes (Rao, and, Aparn, 2023), Difficulty in segmenting small, variable brain areas like the hippocampus (Rao, and, Aparn, 2023).

2.2 Artificial Intelligence for Detecting Cognitive Impairment

Current research has concentrated on utilizing deep learning for the early detection of cognitive impairments. Deep learning CNN model for Alzheimer's disease classification used (Battineni, Chintalapudi, et al. , 2021), this paper has limitation Lack of comparison with other deep learning models. Research on early detection of cognitive impairment has habitually been trained in expert evaluations, clinical assessments and cognitive tests. With the rapid growths of machine learning, scientists have shifted toward data-driven simulations. Deep learning models, exceptionally in the domain of NLP and organized data analysis, have shown potential in extracting samples that could indicate cognitive skill decline.

Existing methods works have employed various techniques, including NLP (Shan, Zhang, et al. , 2022) Random Forest(Niyas, Thiyagarajan, et al. , 2023), Naïve Bayes Classification (Mayilvaganana, Kalpanadevib, et al. , 2015), decision trees, support vector machines (SVM) (Niyas, Thiyagarajan, et al. , 2023), simple CNN(Battineni, Chintalapudi, et al. , 2021). However, latest transformer deep learning models like BERT and GPT, as well as RNN-based architectures like GRU and LSTM, have not been broadly compared in this specific task of cognitive skill impairment detection.

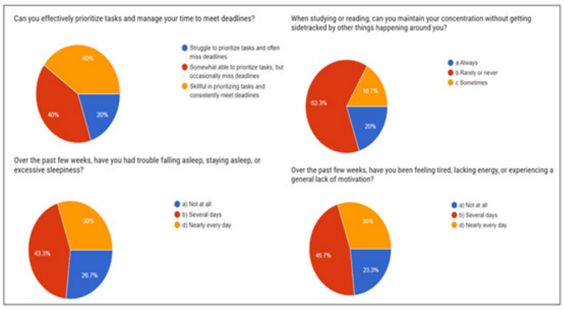

Figure 2: Key Finding of Survey Conducted

2.3 Survey Design and Study Area

This research conducted in-person interviews with different participants located in Senior Citizen Park, Old age home centres and Hospitals. As shown in Fig 2 the survey is conducted for age between 50 to 65 in order to determine the necessity early detection of cognitive skill impairment . It is observed that there are 40 % peoples are somewhat able to prioritize tasks but occusionally miss dedalines.It is also observed that 30% people have trouble falling asleep or excessive sleep.As Fig 2 also shows that 63 % peoples are rarely able to concentration without getting distracted.Overall observation of this fig is there is need to early detection of cognitive skill impairement.

3 PROPOSED METHODOLOGY

3.1 Dataset Preparation

The study included individuals aged 60 years or older. Those who stated latest head damage in the past few months or were confined to bed due to any neurological disorder were excluded from the research study. For dataset collection propsed research work mainely focus on three categories i.e. normal group,mild cognitive skill impairement group and severe cognitive skill impairement group as follows.

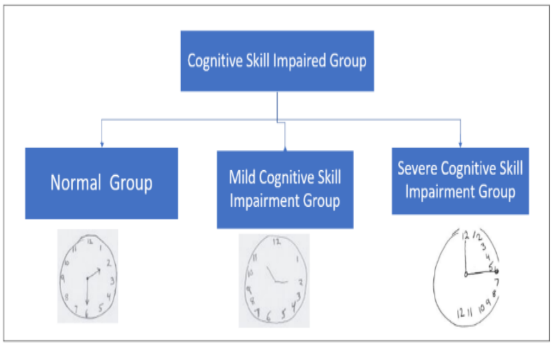

Figure 3: Sample Collection Categories

The dataset used in this study contains demographic information, health-related features and some questionnaires to conduct Cognitive Test

3.2 Dataset Description

The feature set of datasets as follows:

Table 1: Feature Set of Dataset

Variable	Type	Description
Age	Numerical	Respondent's age (integer value).
Gender	Categorical	Gender of the respondent (e.g., Male, Female, Other).
Are you working anywhere?	Categorical	Working status (e.g., working, Unemployed, Student, Retired, etc.).
Are you Married?	Binary	Marital status (1: Married, 0: Not Married).
Are you BP Patient?	Binary	High blood pressure status (1: Yes, 0: No).
Are you Diabetic Patient?	Binary	Diabetes status (1: Diabetic, 0: Non-Diabetic).
Do you have Family History of cognitive skill impairment?	Binary	Family history of cognitive skill impairment (1: Yes, 0: No).
Cognitive Test Score	Numerical	Score obtained from test
Have you diagnosed depression?	Binary	Depression diagnosis (1: Yes, 0: No).
Cognitive skill Impairment Level	Target (Categorical)	The level of cognitive skill impairment

Dataset is intended to design to measures different cognitive skill such as memory, attention, logical reasoning, and problem-solving. For the cognitive test preparation total 15 questions are used for different cognitive skill such as Problem solving, logical Reasoning, Attention, Concentration and Memory. Total marks of Cognitive test are 30.

3.3 Classification of Cognitive skill Impairment Levels Based on Cognitive test Scores

Initially person must attempt a cognitive test. The Cognitive test includes 15 questions of 30 marks. The cognitive skill impairment levels are classified based on the obtained scores as depicted in the figure 4.

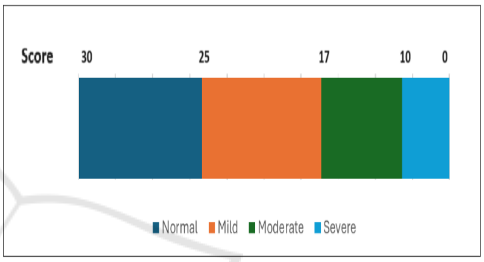

Figure 4: Classification of Cognitive skill Impairment

4 SYSTEM ARCHITECTURE

The historical data is separated into training and testing dataset. Proposed Model is trained using Deep learning algorithm which is ready to accept user data. Incoming User data is applied to trained model which is ready to predict cognitive skill impairment level. Proposed model implementation and algorithm will discuss in next section.

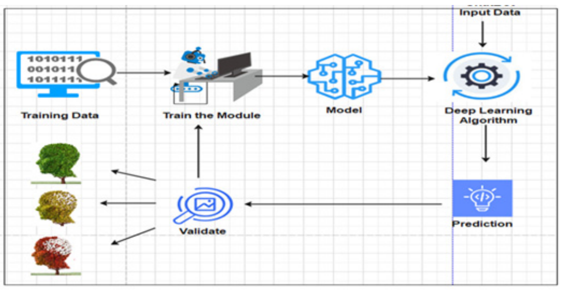

Figure 5: System Architecture

4.1 Algorithm

In this research work Deep learning algorithm was randomly assigned to training 80% and testing 20%.

Model is built using training data and testing data are used to measure the prediction error and overtraining also. This paper employed several deep learning architectures to process different types of data and extract meaningful patterns for the early detection of cognitive skill impairment. The algorithms used include Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), Generative Pretrained Transformers (GPT), Long Short-Term Memory Networks (LSTM), and Convolutional Neural Networks (CNN). Each of these models was selected for its specific ability to process and analyse sequential, time-series, or structured data associated with cognitive decline.

4.1.1 Recurrent Neural Networks (RNN)

RNNs have been utilized to determine sequential medical history that might identify early recognition of cognitive impairment by just inspecting the progression of cognitive decline based on prior health conditions.

4.1.2 Gated Recurrent Units (GRU)

By utilizing gates, GRUs would be able to deal with moderate sequential dependencies during the progression of dementia. They have been applied in patient time-series data that tracked symptoms and medical histories over a period, maintaining a balance between computational efficiency and performance.

4.1.3 Generative Pretrained Transformer (GPT)

GPT was mainly in the process of processing natural language data, which included patient responses in chatbot interactions. The model analysed the conversational data, thus detecting subtle changes in linguistic signs indicating cognitive decline, such as word choice, sentence structure, and flow of conversations. It proved to be an essential component in the detection of early cognitive impairments based on free-text responses.

4.1.4 Long Short-Term Memory Networks (LSTM)

LSTMs were applied to capture long-term patient data. This model comes in handy if the data points show some longer trends, like gradual cognitive decline that spreads over months or years.

4.1.5 Convolutional Neural Networks (CNN)

CNNs have been adopted in this study for processing structured demographic and health data, after extracting the relevant features related to cognitive impairment. The hierarchical nature of CNNs allows automated detection of patterns in variables like age, medical history, and lifestyle, contributing to the overall predicting of risks toward potential cognitive impairments.

5 RESULT AND DISCUSSION

Table 2: Performance Comparison

Algorithm	Accuracy	Precision	Recall (Sensitivity)	F1-Score	Matthews Correlation Coefficient	Memory Usage
RNN	0.992	0.992	0.992	0.992	0.987	103 MB
GRU	0.987	0.987	0.987	0.987	0.979	145 MB
GPT	0.985	0.983	0.988	0.985	0.977	185 mb
LSTM	0.988	0.989	0.988	0.988	0.982	180 MB
CNN	0.985	0.986	0.985	0.985	0.977	176 MB

The performance of various deep learning algorithms—RNN, GRU, GPT, LSTM, and CNN—was evaluated based on several classification metrics: accuracy, precision, recall (sensitivity), F1-score, Matthews Correlation Coefficient (MCC), and memory usage. These metrics provide a comprehensive overview of the models' effectiveness, efficiency, and suitability for detecting cognitive skill impairment in individuals.

5.1 Model Performance

RNN had the best overall performance as its accuracy, precision, recall (sensitivity), and F1-score were reported at 99.2%, respectively. Moreover, the model's MCC was at 0.987, which means a strong correlation existed between the true labels and predicted labels. The high recall and precision of the RNN indicate that it provides an about-equitable balance between false positives and false negatives, making it a sound model for detecting early impairment in cognitive skills. Memory usage by

RNN was measured to be 103 MB, which is relatively moderate compared to the other models.

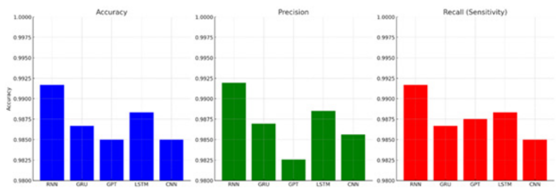

Figure 6:. Model's Performance Evaluation Analysis

GRU does similarly with an accuracy of 98.7%, a precision of 98.7%, a recall of 98.7%, and F1-score of 98.7%. MCC value is 0.979, again very good but slightly less than that of RNN. Thus, despite these minor differences, GRU gets close to being identical to the results obtained by RNN for all classification metrics. However, the reported memory usage for GRU was surprisingly negative (-145 MB), which might indicate some anomaly in measurement or system-specific issues. Further investigation into the model's memory consumption would be required to address such discrepancy. For GPT, the result was slightly lower than for RNN and GRU, at 98.5% accuracy, 98.3% precision, 98.8% recall, and 98.5% F1-score, with the MCC at 0.977, also indicating a drop in robustness of the model as compared to the RNN and GRU. Memory usage for GPT was higher, at 185 MB, which is within expectations due to its large transformer architecture. Even though the performance remains strong, the higher memory requirement might limit the applicability in resource-constrained environments' is basically similar with GPT where accuracy of the model remained at 98.8%, precision was at 98.9%, recall was also at 98.8%, and F1-score at 98.8%. The MCC that comes with the model is 0.982, which reflects strong classification reliability. However, on the other hand, memory consumption of 180 MB is hefty, which demonstrates that a model as efficient as the LSTM may consume many resources. CNN was able to attain an accuracy of 98.5%, precision of 98.6%, recall of 98.5%, and F1-score of 98.5%. MCC of 0.977 for CNN matches well with GPT, hence putting CNN on par in terms of classification quality with other models. But memory usage at 176 MB is reasonable but stays above the RNN which might make CNN less preferable for deployment in memory-limited environments.

6 CONCLUSION AND FUTURE SCOPE

Each of these algorithms was selected based on its ability to model different aspects of the data related to cognitive skill impairment. While RNN, GRU, and LSTM excel in handling sequential data, GPT focuses on capturing complex linguistic patterns from conversational data, and CNN is effective in extracting features from structured medical data. Together, these models provide a comprehensive approach to early detection of cognitive impairment by leveraging both time-series and text-based patient information.

The future scope of this research would be expansion of the datasets for diverse populations and deployment of the models in telemedicine and mobile health apps will bridge the gap between research and practice, ensuring equitable and ethical use.

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