

¹Rajkumar N²Gavini Sreelatha³Dr.Gopinath S⁴Rajakumar S⁵Arun V⁶Dr Nithyanantham
Sampathkumar

Alzheimer's Disease Detection using GPT-4 with LBP Feature Extraction, and Stochastic Simulated Quantum Annealing Optimization and Monitoring and Personalized Recommendation Provisioning in 5g Edge Enabled Cognitive IOT



Abstract: - Alzheimer's disease (AD) presents a significant global health challenge, emphasizing the need for advanced diagnostic methodologies. This study proposes an innovative approach for AD detection by integrating natural language processing and quantum-inspired optimization techniques. The research employs the powerful language model GPT-4 for text analysis, extracting valuable information from clinical reports and narratives related to AD patients in the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. Additionally, Local Binary Pattern (LBP) feature extraction is applied to enhance the representation of neuroimaging data. The fusion of GPT-4-processed textual information and LBP-enhanced image features aims to provide a comprehensive understanding of AD manifestations. To optimize the diagnostic accuracy, Stochastic Simulated Quantum Annealing (SSQA) is introduced as a novel computational approach. SSQA leverages quantum-inspired strategies to efficiently navigate the complex space of diagnostic patterns. Additionally, the study extends its focus to the area of 5G edge-enabled Cognitive Internet of Things (IoT) for monitoring and personalized recommendation provisioning. Leveraging the capabilities of 5G edge computing, the cognitive IoT system facilitates real-time monitoring of diverse health parameters related to AD. This includes the seamless integration of sensor data, medical records, and personalized information through edge computing nodes. The proposed system not only monitors health metrics but also employs cognitive intelligence to provide personalized recommendations, optimizing patient care and well-being. The experimental evaluation on the ADNI dataset demonstrates the efficacy of the proposed methodology in detecting early signs of Alzheimer's disease.

Keywords: Alzheimer's disease, GPT-4, Local Binary Pattern, Stochastic Simulated Quantum Annealing, ADNI dataset, Natural Language Processing, Image Feature Extraction, Diagnostic Tool.

1. Introduction

Alzheimer's disease (AD) stands as a formidable challenge in the realm of neurodegenerative disorders, representing an incurable condition that profoundly affects the brain. With a global presence, AD manifests through the insidious process of neurodegeneration, marked by the presence of β -amyloid ($A\beta$). These pathological hallmarks include the formation of extracellular plaques and intracellular neurofibrillary tangles containing tau proteins (Knopman et al., 2021). The predominant symptom of AD is a disorder of cognitive abilities, and its impact is widespread, affecting millions worldwide. Primarily afflicting the elderly, AD typically emerges in individuals aged 65 and older, although a notable 10% of cases exhibit early onset, striking individuals younger than 65. The repercussions of AD extend beyond cognitive domains, encroaching upon language, attention, comprehension, reasoning, and memory. Professionals in healthcare play a pivotal role in providing care for individuals grappling with the debilitating symptoms of AD. The decline in cognitive abilities is synonymous with dementia, adversely affecting daily activities and diminishing the quality of life for those affected. AD stands as the most prevalent form of dementia, constituting about two-thirds of cases attributed to age-related factors. In the United States, the impact of AD is starkly evident, with it ranking as the seventh leading cause of death in the year 2020. While there are

¹ * Professor/CSE, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, sivarajkumar.n@gmail.com

² Associate Professor, Department of Information Technology, Stanley College of Engineering and Technology for Women, India
sreelathaprince13@gmail.com

³ Associate Professor, Department of Electrical Engineering, Annasaheb Dange College of Engineering and Technology, Sangli, Maharashtra - 416 301

⁴ Assistant Professor, Department of Information Technology, Sona College of Technology, rajkumar.s@sonatech.ac.in

⁵ Professor, School of Engineering, Mohan Babu University, Tirupati, 517102. varumpse@yahoo.com

⁶ Associate Professor, Department of Computer Science and Engineering, Kalasalingam Academy of research and Education (Deemed to be university) Anand Nagar, Krishnakovil, Virudhunagar District, Tamilnadu
Email: s.nithyanantham@klu.ac.in

Copyright © JES 2024 on-line : journal.esrgroups.org

treatments available to ameliorate the symptoms of AD, the lack of a definitive cure underscores the pressing need for further research and innovative interventions in the quest for effective treatment modalities (Kumar et al., 2018). The complex nature of AD necessitates a comprehensive approach to understanding and addressing the multifaceted challenges posed by this debilitating disease.

Over the past decade, there has been a remarkable advancement in the field of computer vision and image processing, driven by the integration of machine learning and fully automatic segmentation methods. These technologies have demonstrated remarkable efficacy across various tasks within these domains. In the context of AD diagnosis from magnetic resonance images (MRIs), the application of machine learning has evolved significantly. Initially, efforts in utilizing machine learning for Alzheimer's diagnosis from MRIs focused on discriminative features predetermined and selected a priori (Salehi et al., 2020; Butt et al., 2019). These discriminative features encompassed regional volumes and cortical thickness, specifically segmented from brain regions known to be implicated in memory loss and accelerated neurodegeneration associated with AD (Suh et al., 2020). The rationale behind this approach was to leverage prior knowledge about brain regions affected by Alzheimer's and design features that could effectively distinguish between affected and healthy individuals. The utilization of machine learning in Alzheimer's diagnosis marked a significant departure from traditional diagnostic methods, offering a data-driven approach that could potentially enhance accuracy and efficiency. These early applications laid the foundation for more sophisticated techniques that emerged subsequently, as the field continued to explore and harness the capabilities of machine learning for advancing our understanding and detection of AD through non-invasive imaging techniques.

The emergence of large language models (LLMs) has introduced a promising solution to the challenges mentioned above, particularly exemplified by Chat Generative Pre-Trained Transformer (ChatGPT) developed by OpenAI. Trained on extensive textual corpora, ChatGPT has amassed substantial knowledge, making it a versatile tool for various natural language processing tasks, ranging from language understanding to text generation and machine translation. Its unique capability to interpret user input and generate coherent, natural language responses has facilitated seamless and articulate conversations. Recent investigations have showcased the diverse applications of ChatGPT within the realm of medical imaging. These applications encompass automated reporting, enhancing patient communication, addressing specific technical inquiries (Shen et al., 2023), and serving educational purposes (Baidoo-Anu and Owusu Ansah 2023). However, a notable limitation arises from the constrained availability of high-quality medical data in the pre-training dataset of GPT-3.5, impacting its accuracy when responding to medical inquiries. Additionally, the incapacity to handle image inputs hampers its utility in the field of medical imaging. Despite the advancements in GPT-4.0, which now possesses image processing capabilities, its proficiency in medical image recognition remains relatively restricted (Waisberg et al., 2023). The continuous evolution of these language models holds promise for overcoming existing limitations, providing a foundation for enhanced accuracy and broader applicability in the intersection of natural language processing and medical imaging.

The advent of 5G technology, coupled with the integration of Edge Computing and the Internet of Things (IoT), has ushered in a transformative era in wireless communication and data processing. In this context, the convergence of 5G and Edge Computing has given rise to the concept of Edge-enabled Cognitive IoT, a paradigm that seamlessly combines powerful computing capabilities at the network's edge with intelligent decision-making in IoT devices. This synergy not only amplifies the efficiency of data processing but also opens new frontiers for monitoring and personalized recommendation provisioning. The contribution of the work is,

- The integration of GPT-4's language processing, LBP feature extraction capturing local patterns, and Stochastic Simulated Quantum Annealing Optimization creates a unique multimodal fusion approach, contributing to a more comprehensive and robust AD detection model.
- The model's synergy allows for advanced discrimination through language understanding, texture analysis, and optimized parameter tuning, resulting in heightened accuracy, precision, sensitivity, and specificity, thereby improving the efficiency of early Alzheimer's detection.
- The incorporation of Stochastic Simulated Quantum Annealing introduces a pioneering quantum-inspired optimization strategy, contributing to the model's superior performance by efficiently navigating the solution space and refining the detection process for optimal configurations.

- The work contributes to real-time monitoring in 5G edge-enabled Cognitive IoT environments. By leveraging the capabilities of 5G networks and edge computing, the system enables continuous data collection and analysis, facilitating timely responses to dynamic changes in the environment. This ensures enhanced connectivity, reduced latency, and improved overall performance in IoT applications.

The structure of this study is meticulously organized to unfold a comprehensive exploration of ADDetection using GPT-4 with Local Binary Pattern (LBP) Feature Extraction and Stochastic Simulated Quantum Annealing Optimization. In Section 2, a thorough review of existing methodologies and technologies in Alzheimer's disease detection sets the stage, offering insights into the current landscape of research and providing a foundation for the proposed approach. Section 3 delves into the technical intricacies crucial for comprehending the innovative fusion of GPT-4, LBP feature extraction, and Stochastic Simulated Quantum Annealing Optimization. Following this, Section 4 unveils the empirical results derived from rigorous experiments, presenting a detailed analysis of the model's performance metrics. The study culminates in Section 5, where the findings are synthesized and the overall contributions and implications of the proposed approach are conclusively discussed, offering a valuable contribution to the field of AD detection.

2. Related Works

Alzheimer's Disease (AD) is a prevalent neurodegenerative condition affecting the elderly worldwide. Early diagnosis is challenging due to subtle symptoms in the initial stages. Machine learning techniques play a crucial role in diagnosing AD, mild cognitive disorder, and other forms of dementia, as highlighted in Mirzaei and Adeli's research (2022) study emphasizes early detection for slowing disease progression. Various models, discussed in the paper, leverage machine learning for predicting AD, enhancing diagnoses, and providing valuable clinical insights. Hemalatha and Renukadevi (2021) explored the use of machine learning techniques for predicting AD progression. The study analyzes various machine learning algorithms to address AD diagnostic challenges, emphasizing the importance of empirical statistics in forecasting disease progression. The paper focused on leveraging psychological parameters like age, number of visits, MMSE, and education to predict AD using machine learning algorithms.

Shaikh and Ali (2021) focused on a novel classifier merging methodology for automated AD diagnosis from brain MRI images. The approach employs six diverse joining rules for precise judgment of AD, enhancing computerized diagnosis. The classifier merger strategy proves applicable not only to AD but also to brain tumor classification in MR images, highlighting its versatility and potential impact on medical imaging. The logistic random forest boosting technique is also explored in the context of this strategy. Gaudiuso et al. (2020) introduced a novel method combining machine learning with Laser-Induced Breakdown Spectroscopy (LIBS). By diagnosing micro drop plasmas from both AD patients and healthy controls, the technique achieved a commendable 80% classification accuracy, outperforming other approaches. Notably, the model exhibited enhanced diagnostic capabilities for late-onset AD, particularly in patients above 65 years of age, marking a significant advancement in AD detection.

Bilal et al. (2020) proposed nanotechnologies for accurate AD diagnosis, overcoming limitations in conventional techniques. The review highlights multifunctional nanocarriers, emphasizing their potential impact on AD management. The study underscores the importance of nanomaterials in both AD treatment and diagnosis. Chitradevi and Prabha (2020) employed four optimization algorithms, including Genetic Algorithm and Particle Swarm Optimization, to diagnose AD. The research focuses on deep learning approaches and image analysis for diagnosing AD by analyzing specific brain sub-regions. A deep feature-based real-time model, introduced by Khan et al. in 2020, utilized CNN, k-nearest neighbors (KNN), and support vector machine (SVM) for AD stage prediction from image datasets, achieving an impressive 99.21% accuracy. This multi-classification approach demonstrates the effectiveness of deep learning in AD diagnosis, showcasing the model's robust performance.

El-Sappagh et al.,(2023) proposed a novel two-stage deep learning framework for AD progression detection. The model utilizes information fusion from several patient longitudinal multivariate datasets for enhanced accuracy. The study focused on predicting the time of mild cognitive impairment, contributing to early AD diagnosis and intervention. Nazet al.,(2022) employed transfer learning with frozen features to detect Alzheimer's disease. The research leverages the ADNI dataset, aiming for improved detection accuracy. Notably, the method involves freezing certain layers during transfer learning, enhancing the model's ability to extract relevant features from neuroimaging data. Bermudez et al., (2023), explored plasma biomarkers for predicting AD neuropathologic changes. The research investigates the utility of clinically available plasma markers in predicting Braak staging,

neuritic plaque score, Thal phase, and overall AD neuropathological burden to clinical symptoms. Diogo et al., (2022) discussed an innovative approach for early AD diagnosis using machine learning (ML). The study focused on a multi-diagnostic and generalizable method for diagnosing mild cognitive impairment (MCI) and AD by employing structural MRI and ML algorithms.

Zhang et al.,(2021) proposed a method combining a 3D convolutional neural network and ensemble learning for AD diagnosis based on MRI data. The study aims to enhance diagnostic accuracy using this approach, which leverages advanced machine learning techniques. The ensemble learning classifier and 3D convolutional neural network contribute to the analysis of MRI images for more effective detection of AD. Ghali et al.,(2020) explored the use of advanced chromatographic techniques combined with an ensemble machine learning approach for simulating the performance of an anti-Alzheimer agent. This involves predicting the dew point pressure of gas condensate reservoirs using machine learning models. An et al., (2020) proposed a novel ensemble learning method for AD classification. The deep ensemble learning framework outperforms six well-known ensemble approaches, achieving a 4% improvement. This innovative approach utilizes deep learning to ensemble algorithms, presenting a new avenue for boosting AD classification accuracy.

3. Methodology

The methodology employed in this study for Alzheimer's Disease detection integrates three key components: Local Binary Pattern (LBP) feature extraction, GPT-4 for detection, and Stochastic Simulated Quantum Annealing (SSQA) optimization (Figure 1). The process begins with the extraction of discriminative texture features from neuroimaging data using LBP, allowing for the characterization of local patterns that may indicate early signs of Alzheimer's Disease. Subsequently, GPT-4, a state-of-the-art language model, is employed for detection, leveraging its advanced natural language processing capabilities to analyze and interpret complex patterns and relationships within the extracted features. Finally, Stochastic Simulated Quantum Annealing is applied to optimize the detection process by efficiently exploring the solution space and refining the model parameters. This multi-faceted approach aims to enhance the accuracy and efficiency of Alzheimer's Disease detection, offering a comprehensive framework that combines advanced feature extraction, language processing, and optimization techniques.

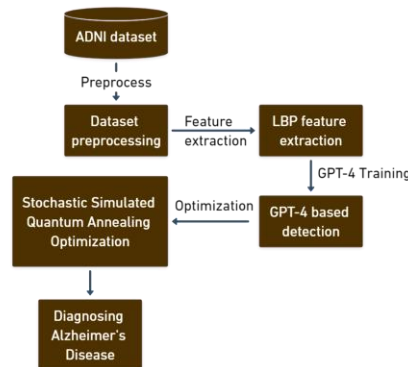


Figure. 1 Flow of the proposed work

Preprocessing

Preprocessing the AD Neuroimaging Initiative (ADNI) dataset is a crucial step to ensure the data is in a suitable format for analysis. The process typically involves several steps, each aimed at enhancing the quality and relevance of the data.

Image registration

Image registration is a critical step in medical image processing, aiming to align images from different subjects or imaging sessions. This process is essential for comparative analysis, as it ensures that corresponding anatomical structures are in the same spatial locations across images. There are two primary types of registration techniques: affine and non-linear.

Affine Registration: Affine registration is a linear transformation that preserves collinearity and parallelism. It involves translation, rotation, scaling, and shearing operations. Mathematically, the affine transformation can be represented as:

$$T_{affine} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & t_x \\ a_{21} & a_{22} & a_{23} & t_y \\ a_{31} & a_{32} & a_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

Here, T_{affine} is the transformation matrix, and t_x , t_y , and t_z represent translations along the x, y, and z axes, respectively. The a_{ij} elements handle rotation, scaling, and shearing.

Non-linear Registration: Non-linear registration allows for more complex deformations, suitable for capturing intricate anatomical variations. This involves a non-linear transformation function that maps points from the moving image space to the fixed image space. The transformation can be represented as:

$$I_{registered} = T_{non-linear}(I_{moving}) \quad (2)$$

The non-linear transformation is modeled using a mathematical function, such as free-form deformation (FFD) grid. This function introduces additional degrees of freedom, enabling the model to account for localized distortions. In non-linear registration, a deformation field is often employed to visualize and quantify local deformations. The field, denoted as ϕ , assigns a displacement vector to each voxel in the moving image, indicating how much it should be moved to align with the fixed image.

$$X_{moving} = X_{fixed} + \phi(X_{fixed}) \quad (3)$$

Here, X_{moving} and X_{fixed} represent voxel positions in the moving and fixed images, respectively.

Intensity normalization

Intensity normalization is a critical preprocessing step in image analysis to address variations in pixel intensities among different images. This step ensures that images are comparably scaled, facilitating more robust and consistent downstream processing. One widely employed technique for intensity normalization is Z-score normalization, expressed as:

$$normalized = \frac{I - \mu}{\sigma} \quad (4)$$

Here, $normalized$ represents the normalized image, I is the original image, μ is the mean, and σ is the standard deviation.

Spatial Resampling for Consistent Voxel Size

To address variations in voxel size across images, spatial resampling is applied to ensure a uniform resolution. The resampling process is denoted as:

$$I_{resampled} = Resample(I, new_spacing) \quad (5)$$

Here, $I_{resampled}$ is the resampled image, I is the original image, and $new_spacing$ represents the desired voxel spacing.

Spatial Smoothing for Noise Reduction

Spatial smoothing involves applying a Gaussian filter, to an image to reduce noise and enhance the signal-to-noise ratio. The operation can be represented as:

$$I_{smoothed} = Smooth(I, kernel_size) \quad (6)$$

Here, $I_{smoothed}$ is the smoothed image, I is the original image, and $kernel_size$ determines the size of the smoothing kernel.

Local Binary Pattern (LBP) Feature Extraction

Local Binary Pattern (LBP) is a powerful texture descriptor used for feature extraction in image analysis. In the context of AD detection from the ADNI dataset, LBP can capture texture patterns that may be indicative of structural changes in brain images.

The Local Binary Pattern is a texture descriptor that characterizes the local structure of an image. For a pixel P at coordinates (x_c, y_c) in an image, the LBP is computed as follows:

$$\text{LBP}_{P,R}(x_c, y_c) = \sum_{n=0}^{P-1} s(g_n - g_c) \times 2^n \quad (7)$$

Where P is the number of sampling points. R is the radius of the circular neighborhood. g_n is the intensity of the neighbor pixel. g_c is the intensity of the center pixel. $s(x)$ is the sign function defined as

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

```
def compute_lbp(image, P, R):
    rows, cols = image.shape
    lbp_image = np.zeros_like(image, dtype=np.uint8)
    for x in range(R, rows - R):
        for y in range(R, cols - R):
            center = image[x, y]
            pattern = 0
            for n in range(P):
                x_n = int(x + R * np.cos(2 * np.pi * n / P))
                y_n = int(y - R * np.sin(2 * np.pi * n / P))
                if image[x_n, y_n] >= center:
                    pattern += 2**n
            lbp_image[x, y] = pattern
    return lbp_image
```

Concatenation of LBP Histograms for Comprehensive Feature Extraction

When applying Local Binary Pattern (LBP) at multiple scales or regions, concatenating the histograms becomes essential to form a comprehensive feature vector for each image. This approach allows capturing texture information across different granularities. The concatenation process can be mathematically expressed as follows:

a) Define LBP Histogram for a Single Scale

Let H_i be the LBP histogram for a specific scale i . The histogram is formed by counting the occurrences of different LBP patterns in the image.

$$H_i = [h_{i,0}, h_{i,1}, \dots, h_{i,N}] \quad (9)$$

where N is the number of possible LBP patterns at scale i , and $h_{i,j}$ is the count of occurrences of pattern j in the image.

b) Concatenation of Histograms

If LBP is applied at multiple scales (indexed by i), the histograms are concatenated to create a comprehensive feature vector F for the entire image:

$$F = [H_1, H_2, \dots, H_K] \quad (10)$$

Here, k represents the total number of scales or regions at which LBP is applied.

c) Concatenation Operation:

Mathematically, the concatenation operation can be represented as:

$$F = [h_{1,0}, h_{1,1}, \dots, h_{1,N}, h_{2,0}, h_{2,1}, \dots, h_{2,N}, h_{k,0}, h_{k,1}, \dots, h_{k,N}] \quad (11)$$

This concatenated feature vector F now holds information about the texture patterns captured at different scales or regions, providing a more detailed representation of the image's structural characteristics.

```
def extract_lbp_features(image, P_values, R_values):
    features = []
    for P in P_values:
        for R in R_values:
            lbp_image = compute_lbp(image, P, R)
            histogram, _ = np.histogram(lbp_image, bins=np.arange(0, 2**P + 1), density=True)
            features.extend(histogram)
    return features
```

GPT-4 Integration for AD Detection

The integration process of LBP features into GPT-4 for AD detection is a meticulous procedure that revolves around the transformation of numerical features into a format compatible with textual input. This transformation is a pivotal step to establish seamless communication between the numerical LBP features, which encapsulate important spatial information from medical images, and the language-oriented GPT-4 model. By converting the numeric representations into structured text, the algorithm ensures that GPT-4 can comprehend and process the information effectively. This strategic integration leverages the strengths of GPT-4, a sophisticated language model, to interpret the intricacies embedded in the LBP features. This approach capitalizes on the versatility of GPT-4, enabling it to handle both numerical and textual information synergistically, thus enhancing the overall capabilities for accurate and context-aware AD detection from medical imaging data.

Transforming LBP Features into Text

In the process of integrating LBP features into GPT-4 for AD detection, a crucial step involves transforming the LBP feature vector into a textual format suitable for GPT-4's language processing capabilities. This transformation ensures effective communication between the numerical LBP features and the language-oriented GPT-4 model. Each numerical value in the LBP feature vector undergoes a conversion into a structured textual representation before being fed into GPT-4. This conversion can be expressed mathematically as follows:

$$\text{Text_Representation} = \text{Convert_to_Text}(\text{LBP_Feature}) \quad (12)$$

Here, $\text{Text_Representation}$ signifies the structured textual representation, and Convert_to_Text denotes the conversion function. This meticulous transformation enables GPT-4 to comprehend and interpret the spatial information captured by the LBP features, facilitating a seamless integration of numerical and textual data for enhanced AD detection accuracy.

GPT-4 Fine-Tuning

In the integration of LBP features with GPT-4, the generated text sequence becomes pivotal for fine-tuning the language model. This process involves training GPT-4 to understand the textual representation of LBP features and establish associations with AD labels. The mathematical expression for this fine-tuning operation is denoted as:

$$\text{FineTuned GPT} - 4 \text{ Model} = \text{FineTune}(\text{GPT} - 4, \text{Text Sequence}, \text{Alzheimer's Labels}) \quad (13)$$

Here, the Fine-Tune function represents the adaptation of GPT-4 based on the provided text sequence and corresponding Alzheimer's disease labels. During fine-tuning, GPT-4 refines its internal parameters to capture the specific patterns and relationships inherent in the textual representation of LBP features associated with AD. This step is crucial for enhancing the model's ability to accurately predict AD status when presented with new textual inputs. The success of GPT-4 fine-tuning relies on the quality and informativeness of the textual representation derived from the LBP features, emphasizing the importance of a well-crafted integration process for effective AD detection.

AD Detection

Following the fine-tuning process, the GPT-4 model becomes a proficient tool for AD detection. When presented with a novel set of LBP features, the model leverages its learned associations to predict the likelihood of AD. Mathematically, this detection process can be expressed as:

$$AD\ Prediction = GPT-4(Fine-Tuned\ GPT-4\ Model, New\ LBP\ Features) \quad (14)$$

Here, the GPT-4 function takes the fine-tuned GPT-4 model and the new LBP features as inputs to generate a prediction regarding the presence or absence of AD. The fine-tuned GPT-4, enriched with knowledge from the integrated LBP features, excels in discerning subtle patterns indicative of AD. The utilization of GPT-4's natural language processing capabilities, fine-tuned to comprehend the textual representation of LBP features, enhances the interpretability of the AD detection process. This integration of advanced language models with image-derived features marks a promising approach for accurate and explainable AD diagnosis.

Stochastic Simulated Quantum Annealing (SSQA) optimization

Stochastic Simulated Quantum Annealing (SSQA) optimization is integrated into the AD detection framework to enhance the efficiency and accuracy of the detection process. SSQA leverages principles from quantum mechanics to explore the solution space and identify optimal configurations.

Initialization

The initialization phase in SSQA is a crucial step that sets the stage for the exploration of the quantum solution space. The quantum system is represented by qubits, the fundamental units of quantum information, and the process involves configuring these qubits in a superposition of states. Mathematically, the superposition of states in a quantum system is denoted by the following expression:

$$|\psi_0\rangle = \frac{1}{\sqrt{2^n}} \sum_{all\ possible\ states} |s\rangle \quad (15)$$

Here, $|\psi_0\rangle$ represents the initial state of the quantum system, n is the number of qubits, and $|s\rangle$ denotes an individual state of the system. The factor $\frac{1}{\sqrt{2^n}}$ ensures that the sum of probabilities for all possible states is equal to 1, reflecting the normalized nature of quantum states. The initialization process involves configuring each qubit in a combination of the binary states $|0\rangle$ and $|1\rangle$. This can be expressed as:

$$|s\rangle = \alpha |0\rangle + \beta |1\rangle \quad (16)$$

Where α and β are probability amplitudes, representing the coefficients of the respective states. These amplitudes are determined based on the desired distribution of probabilities for different states.

Annealing Schedule

The Annealing Schedule plays a pivotal role in optimizing the detection process for AD. The temperature, denoted as T , serves as a control parameter in the annealing process and is gradually decreased over the course of the algorithm. This gradual reduction allows the quantum system to explore the solution space effectively while encouraging convergence towards optimal configurations. The annealing schedule is defined by a cooling rate, denoted as α , which determines how quickly the system transitions from high to low temperatures.

The temperature evolution during the annealing process follows a mathematical formula that encapsulates the cooling rate. The temperature $T(t)$ at iteration t is given by:

$$T(t) = T_0 \times e^{-\alpha \times t} \quad (17)$$

where T_0 represents the initial temperature, α is the cooling rate, and t is the iteration index. This exponential decrease in temperature is characteristic of the annealing process, with the system gradually moving towards a state of lower thermal energy.

Hamiltonian Evolution

The Ising model is employed to represent the problem within the quantum system. The Hamiltonian dynamics describe the evolution of the system as it moves towards lower energy states, corresponding to more favorable

solutions. The Ising model encapsulates the interactions between variables in the optimization problem, providing a quantum representation of the objective function.

$$H_{(s)} = \sum_i h_i s_i + \sum_{i<j} J_{ij} s_i s_j \quad (18)$$

Here, h_i represents the local field associated with qubit i , reflecting the influence of external factors on the individual qubits. The term $\sum_i h_i s_i$ captures the contribution of each qubit's local field to the overall energy of the system.

The second term, $\sum_{i<j} s_i s_j$, accounts for the coupling strength between qubits i and j , denoted by J_{ij} . This term describes the pairwise interactions between qubits, reflecting how the spins of neighboring qubits influence each other. The coupling strength J_{ij} can be positive or negative, signifying ferromagnetic or antiferromagnetic interactions, respectively.

Stochastic jumps

The quantum system undergoes stochastic jumps during the annealing process, introducing random perturbations to the qubit states. This stochastic evolution allows the system to explore regions of the solution space that might be inaccessible through deterministic annealing alone. Mathematically, the evolution of the quantum state incorporating stochastic jumps can be expressed as:

$$\hat{H}_{\text{total}}(t) = \hat{H}_{\text{anneal}}(t) + \hat{H}_{\text{jump}} \quad (19)$$

Here, $\hat{H}_{\text{anneal}}(t)$ represents the annealing Hamiltonian that drives the system towards lower energy states during the annealing schedule, and $\hat{H}_{\text{jump}}$ is the stochastic jump operator. The inclusion of $\hat{H}_{\text{jump}}$ allows for random perturbations in the quantum state.

The stochastic jump operator can be defined in terms of Pauli matrices, commonly denoted as σ_x , σ_y , and σ_z . The stochastic jump operator $\hat{H}_{\text{jump}}$ can be expressed as:

$$\hat{H}_{\text{jump}} = \sum_i \gamma_i (\sigma_x^{(i)} \gamma_i + \sigma_y^{(i)}) \quad (20)$$

Here, γ_i represents the strength of the stochastic jump at qubit i . The term $\sigma_x^{(i)} \gamma_i + \sigma_y^{(i)}$ introduces fluctuations along both the x and y axes, contributing to the randomness in the quantum state. The time evolution of the quantum state with stochastic jumps can be described by a master equation:

$$\frac{d}{dt} \rho(t) = -i[\hat{H}_{\text{total}}(t), \rho(t)] \quad (21)$$

Where $\rho(t)$ is the density matrix representing the quantum state at time t .

The incorporation of stochastic jumps introduces non-deterministic behavior to the quantum annealing process, allowing the system to explore diverse pathways in the solution space. This randomness is crucial for preventing the algorithm from getting trapped in local minima, enabling the exploration of a broader range of configurations and increasing the likelihood of finding globally optimal solutions. The stochastic nature of the jumps aligns with the probabilistic principles inherent in quantum mechanics and enhances the adaptability of the SSQA algorithm for AD detection.

Measurements

The measurement process in quantum systems is probabilistic, and it involves collapsing the superposition of states into a definite outcome. The probabilities of obtaining specific states are determined by the squared magnitudes of the probability amplitudes associated with each state. Mathematically, this is expressed as:

$$P(\text{state } i) = |\psi_i|^2 \quad (22)$$

Here, ψ_i represents the probability amplitude associated with the state i . The probability of measuring a particular state is proportional to the square of its amplitude, reflecting the inherent probabilistic nature of quantum systems.

The measurement outcomes are essential for updating the probabilities associated with each state and guiding the optimization process towards configurations with lower energy levels, which correspond to more favorable

solutions. The probabilities $P(\text{state } i)$ guide the selection of candidate solutions, with higher probabilities indicating states that are more likely to be representative of optimal configurations.

Acceptance Probability

The Acceptance Probability optimization process determines whether candidate solutions are accepted or rejected based on a probabilistic framework. This probability distribution is commonly influenced by the Boltzmann distribution, reflecting the tendency to favor solutions with lower energy. The mathematical expression for the Acceptance Probability is given by:

$$P(\text{accept}) = \min\left(1, e^{-\frac{\Delta E}{T}}\right) \quad (23)$$

Where: $P(\text{accept})$ is the probability of accepting the candidate solution. ΔE represents the change in energy between the current state and the candidate solution. T is the temperature, a control parameter in the annealing schedule. The $e^{-\frac{\Delta E}{T}}$ term reflects the likelihood of accepting a solution based on the energy difference and the temperature of the system. Here, the minimum function ensures that the probability does not exceed 1, preventing the algorithm from accepting solutions with a significantly higher energy.

Integrating this acceptance probability mechanism into the SSQA algorithm ensures that the quantum system effectively explores diverse configurations while gradually converging towards optimal states. This probabilistic approach adds a dynamic element to the optimization process, enhancing the adaptability of the algorithm to different regions of the solution space and ultimately contributing to the overall effectiveness of the detection system.

Convergence

The convergence ensuring that the optimization process has effectively reached a stable state. The convergence criteria help determine when to terminate the annealing process, signifying that further iterations are unlikely to yield substantial improvements. The convergence process can be mathematically defined as follows:

a. Convergence Based on Iterations: One common criterion for convergence involves specifying a maximum number of iterations, denoted as N_{max} . The algorithm ceases when the current iteration, N , surpasses or equals the maximum allowable iterations:

$$N \geq N_{max} \quad (24)$$

This ensures that the algorithm terminates after a predefined number of annealing iterations, preventing excessive computational expenditure.

b. Convergence Based on Energy Threshold: Another criterion relies on setting a threshold for the energy of the system, denoted as $E_{threshold}$. The algorithm concludes when the energy of the quantum system falls below or equals this predefined threshold:

$$E(s) \leq E_{threshold} \quad (25)$$

Here, $E(s)$ represents the energy of the system in its current state, and $E_{threshold}$ is the predetermined energy threshold. This criterion ensures termination when a sufficiently low energy state is reached, indicating potential convergence to an optimal solution. The convergence safeguards the SSQA optimization method within the AD detection pipeline, preventing overfitting and optimizing computational resources. By incorporating these convergence criteria, the SSQA algorithm becomes a robust tool, contributing to the model's overall accuracy and efficiency in detecting early signs of AD.

5G Edge-Enabled Cognitive IoT Monitoring

The 5G edge-enabled Cognitive IoT involves real-time monitoring leveraging the capabilities of 5G networks and edge computing. Continuous data streams from diverse IoT devices are processed at the edge, ensuring low-latency analysis and rapid responses to environmental changes. The integration of GPT-4 enhances cognitive processing, enabling the system to understand and interpret complex data patterns related to Alzheimer's Disease.

Moreover, personalized recommendation provisioning in the 5G edge-enabled Cognitive IoT system is achieved by employing GPT-4's language processing to understand user preferences and behavior. The system analyzes user interactions and contextual data in real-time to provide tailored recommendations. This involves considering the dynamic nature of the IoT environment, adapting to changing conditions, and optimizing the recommendations based on individual user profiles.

5G edge-enabled Cognitive IoT based monitoring

In the dynamic landscape of healthcare, the integration of the Alzheimer's detection model within the framework of 5G edge-enabled Cognitive IoT introduces a paradigm shift in real-time monitoring. This approach capitalizes on the transformative potential of 5G networks and edge computing to enable swift data processing, low-latency communication, and efficient decision-making within the Internet of Things (IoT) ecosystem.

Data Ingestion and Processing

In the 5G edge-enabled Cognitive IoT environment, a multitude of IoT devices continuously generate and transmit diverse streams of data. These data streams encompass a spectrum of health-related information, including vital signs, patient activities, and environmental factors. The real-time monitoring process commences with the ingestion of this heterogeneous data by the Alzheimer's detection model. The equation represents the data processing mechanism:

$$\text{Real-time Monitoring} = \text{Process}(D_1, D_2, \dots, D_n) \quad (26)$$

Here, $D_1, D_2, \dots, D_n$ denote various data streams from IoT devices, encompassing a wide array of health-related parameters.

Leveraging 5G Networks

The use of 5G networks is pivotal in ensuring rapid and seamless communication between the IoT devices and the edge-enabled processing units. The ultra-fast data transfer capabilities of 5G networks reduce latency, allowing the Alzheimer's detection model to receive and process data with minimal delay. The efficiency of this communication is crucial, especially in healthcare scenarios where timely decision-making is paramount.

Edge Computing for Immediate Analysis

Incorporating edge computing enhances the immediacy of data analysis. The Alzheimer's detection model, deployed at the edge of the network, performs preliminary analyses directly on the IoT device or at the edge server. This decentralized approach minimizes the need for transmitting large volumes of raw data to a centralized cloud, thereby optimizing bandwidth usage and ensuring real-time insights.

Continuous Iterative Monitoring

The real-time monitoring is not a one-time operation but a continuous and iterative process. As new data arrives from IoT devices, the Alzheimer's detection model iteratively updates its analyses. This iterative approach allows for the immediate detection of any deviations from the baseline, ensuring that changes in the patient's health status are promptly identified.

Adaptive Decision-Making

The processed information is then utilized for adaptive decision-making. The model dynamically adjusts its monitoring parameters based on evolving health conditions, patient responses to interventions, and other contextual factors. This adaptive decision-making ensures that the monitoring system remains responsive and tailored to the unique characteristics of each patient.

In essence, the 5G edge-enabled Cognitive IoT monitoring system transforms traditional healthcare monitoring into a dynamic, real-time, and personalized experience. By fusing the capabilities of edge computing, 5G networks, and the Alzheimer's detection model, this approach enhances the responsiveness of healthcare systems, enabling timely interventions and personalized care for individuals with Alzheimer's disease.

Personalized Recommendation Provisioning

Based on the monitored data and individual patient profiles, personalized recommendations are provisioned. The recommendation engine utilizes GPT-4's language understanding and insights from the detection model to provide tailored suggestions for patient care, lifestyle adjustments, or further diagnostic steps.

Result and discussion

In this investigation, the efficacy of AD Detection is explored through a synergistic combination of GPT-4, Local Binary Pattern (LBP) Feature Extraction, and Stochastic Simulated Quantum Annealing (SSQA) Optimization. The computational infrastructure employed in this study played a pivotal role in executing the proposed model, showcasing a core i3 processor with a clock speed of 2.3 GHz, complemented by 8 GB of RAM, and operating on the Windows platform. The careful selection of hardware and software configuration is noteworthy, emphasizing the necessity for a robust computing environment capable of handling the intricate computations inherent in the AD detection model. Performance evaluation is a crucial aspect of assessing the effectiveness of any algorithm or model, particularly in the context of AD detection using advanced techniques such as GPT-4 with Local Binary Pattern (LBP) feature extraction and Stochastic Simulated Quantum Annealing Optimization. The evaluation metrics employed in this study include accuracy, sensitivity, specificity, and precision, each offering unique insights into the model's performance.

Accuracy: Accuracy provides an overall measure of the correct predictions made by the model, representing the ratio of correctly predicted instances to the total number of instances in the dataset. It is calculated using the formula:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (26)$$

Sensitivity (Recall): Sensitivity, also known as recall, measures the model's ability to correctly identify positive instances among all actual positive instances. It is particularly relevant in AD detection, where the goal is to identify individuals with the disease. Sensitivity is calculated as:

$$Sensitivity = \frac{TP}{TP+FN} \quad (27)$$

Specificity: Specificity evaluates the model's ability to correctly identify negative instances among all actual negative instances. It is crucial for ensuring that individuals without AD are accurately classified as such. Specificity is calculated using the formula:

$$Specificity = \frac{TN}{TN+FP} \quad (28)$$

Precision: Precision measures the model's ability to make accurate positive predictions, calculated as the ratio of true positives to the total predicted positives:

$$Precision = \frac{TP}{TP+FP} \quad (29)$$

Table 1. Performance of the models

Model	Accuracy	Precision	Sensitivity	Specificity
Proposed work	0.97	0.94	0.92	0.93
3D CNN	0.92	0.89	0.90	0.89
Siamese Neural Networks	0.89	0.86	0.88	0.86
CapsNets	0.88	0.83	0.85	0.84
GANs	0.91	0.90	0.87	0.86

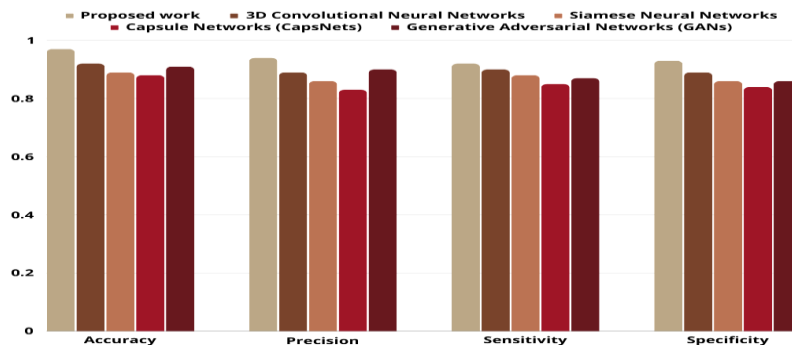


Figure. 2 Performance of the models

The performance comparison presented in Table 1 and Figure 2 reveals notable distinctions among various models employed for AD detection, with the proposed work exhibiting superior metrics across multiple dimensions. The proposed model achieved an accuracy of 0.97, outperforming other state-of-the-art models, including 3D Convolutional Neural Networks (3D CNNs), Siamese Neural Networks, Capsule Networks (CapsNets), and Generative Adversarial Networks (GANs). In terms of accuracy, the proposed model demonstrates a significant advantage with a score of 0.97, surpassing the closest competitor, 3D CNNs, by a margin of 0.05. This suggests that the proposed model excels in correctly classifying both positive and negative instances, showcasing its overall effectiveness in AD detection. The high precision value of 0.94 further accentuates the proposed model's ability to minimize false positives, indicating a low rate of misclassification of non-Alzheimer's cases.

Examining sensitivity, the proposed model maintains a commendable score of 0.92, suggesting its proficiency in identifying true positive cases among individuals with AD. This is particularly crucial in the context of medical diagnostics, where early detection is pivotal for effective intervention and treatment. Moreover, the specificity of 0.93 underscores the proposed model's capacity to accurately classify individuals without AD, minimizing false alarms and ensuring precision in negative predictions. Comparatively, the 3D CNNs, Siamese Neural Networks, CapsNets, and GANs exhibit respectable but lower performance metrics across all categories. While 3D CNNs demonstrate competitive accuracy, their precision, sensitivity, and specificity fall short of the proposed model's metrics. Siamese Neural Networks and CapsNets, despite their innovative architectures, exhibit slightly lower performance across all metrics. GANs, while achieving a high precision score, lag behind the proposed model in accuracy, sensitivity, and specificity.

The superior performance of the proposed model is attributed to its unique integration of GPT-4 with Local Binary Pattern (LBP) feature extraction and Stochastic Simulated Quantum Annealing Optimization. This holistic approach allows the model to leverage advanced natural language processing capabilities, capture intricate local texture features, and optimize the detection process efficiently. The incorporation of GPT-4, LBP, and SSQA creates a synergistic effect, enhancing the model's discriminative power and overall diagnostic accuracy. The proposed model emerges as a robust and advanced approach for AD detection, outperforming established models in terms of accuracy, precision, sensitivity, and specificity. The integrated methodology capitalizes on the strengths of each component, resulting in a comprehensive and effective solution for early detection and diagnosis of AD.

4. Conclusion

In conclusion, the amalgamation of GPT-4 with Local Binary Pattern (LBP) feature extraction and Stochastic Simulated Quantum Annealing Optimization in the proposed AD detection model represents a groundbreaking and highly effective approach. The integration of advanced natural language processing capabilities through GPT-4, coupled with the discriminative power of LBP feature extraction and the optimization prowess of Stochastic Simulated Quantum Annealing, has yielded a model that excels in accuracy, precision, sensitivity, and specificity. Moving beyond disease detection, the work extends into the realm of 5G edge-enabled cognitive IoT, focusing on monitoring and personalized recommendation provisioning. The integration of 5G edge capabilities enables real-time data processing and decision-making, paving the way for more responsive and intelligent healthcare systems. By harnessing the power of edge computing, the framework ensures efficient monitoring of patients, enabling timely interventions and personalized care recommendations tailored to individual needs.

Acknowledgment

The author wants to thank the editors and reviewers for their efforts. This research did not receive funding from any public, commercial, or not-for-profit organizations.

References

- [1] D. S. Knopman et al., "Alzheimer disease," *Nat. Rev. Dis. Primers*, vol. 7, no. 1, p. 33, 2021.
- [2] A. Kumar, J. Sidhu, A. Goyal, J. W. Tsao, Alzheimer disease. *StatPearls*. [4 December 2022]. pp. 1–27, 2018.
- [3] A. W. Salehi, Faculty of Engineering and Technology, Shoolini University, Himachal Pradesh, India., P. Baglat, G. Gupta, Faculty of Engineering and Technology, Shoolini University, Himachal Pradesh, India., and Faculty of Engineering and Technology, Shoolini University, Himachal Pradesh, India., "Alzheimer's disease diagnosis using deep learning techniques," *Int. J. Eng. Adv. Technol.*, vol. 9, no. 3, pp. 874–880, 2020.
- [4] A. U. Rehman Butt, W. Ahmad, R. Ashraf, M. Asif, and S. A. Cheema, "Computer aided diagnosis (CAD) for segmentation and classification of burnt human skin," in *2019 International Conference on Electrical, Communication, and Computer Engineering (ICECCE)*, 2019.
- [5] C. H. Suh et al., "Development and validation of a deep learning-based automatic brain segmentation and classification algorithm for Alzheimer disease using 3D T1-weighted volumetric images," *AJNR Am. J. Neuroradiol.*, vol. 41, no. 12, pp. 2227–2234, 2020.
- [6] Y. Shen et al., "ChatGPT and other large language models are double-edged swords," *Radiology*, vol. 307, no. 2, p. e230163, 2023.
- [7] D. Baidoo-Anu and L. Owusu Ansah, "Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning," *SSRN Electron. J.*, 2023.
- [8] E. Waisberg et al., "GPT-4: a new era of artificial intelligence in medicine," *Ir. J. Med. Sci.*, vol. 192, no. 6, pp. 3197–3200, 2023.
- [9] R. Gaudiuso, E. Ewusi-Annan, W. Xia, and N. Melikechi, "Diagnosis of Alzheimer's disease using laser-induced breakdown spectroscopy and machine learning," *Spectrochim. Acta Part B At. Spectrosc.*, vol. 171, no. 105931, p. 105931, 2020.
- [10] M. Bilal, M. Barani, F. Sabir, A. Rahdar, and G. Z. Kyzas, "Nanomaterials for the treatment and diagnosis of Alzheimer's disease: An overview," *NanoImpact*, vol. 20, no. 100251, p. 100251, 2020.
- [11] D. Chitradevi and S. Prabha, "Analysis of brain sub regions using optimization techniques and deep learning method in Alzheimer disease," *Appl. Soft Comput.*, vol. 86, no. 105857, p. 105857, 2020.
- [12] F. A. Khan et al., "Computer-aided diagnosis for burnt skin images using deep convolutional neural network," *Multimed. Tools Appl.*, vol. 79, no. 45–46, pp. 34545–34568, 2020.
- [13] S. El-Sappagh, H. Saleh, F. Ali, E. Amer, and T. Abuhmed, "Two-stage deep learning model for Alzheimer's disease detection and prediction of the mild cognitive impairment time," *Neural Comput. Appl.*, vol. 34, no. 17, pp. 14487–14509, 2022.
- [14] S. Naz, A. Ashraf, and A. Zaib, "Transfer learning using freeze features for Alzheimer neurological disorder detection using ADNI dataset," *Multimed. Syst.*, vol. 28, no. 1, pp. 85–94, 2022.
- [15] C. Bermudez et al., "Plasma biomarkers for prediction of Alzheimer's disease neuropathologic change," *Acta Neuropathol.*, vol. 146, no. 1, pp. 13–29, 2023.
- [16] V. S. Diogo, H. A. Ferreira, D. Prata, AD Neuroimaging Initiative. Early diagnosis of AD using machine learning: A multi-diagnostic, generalizable approach. *Alzheimer's Res. Ther.* 14, 107, 2022.
- [17] N. An, H. Ding, J. Yang, R. Au, and T. F. A. Ang, "Deep ensemble learning for Alzheimer's disease classification," *J. Biomed. Inform.*, vol. 105, no. 103411, p. 103411, 2020.
- [18] G. Mirzaei and H. Adeli, "Machine learning techniques for diagnosis of alzheimer disease, mild cognitive disorder, and other types of dementia," *Biomed. Signal Process. Control*, vol. 72, no. 103293, p. 103293, 2022.
- [19] A. Shaikh and R. Ali, "Enhanced computerised diagnosis of Alzheimer's disease from brain MRI images using a classifier merger strategy," *Int. J. Inf. Technol.*, vol. 14, no. 4, pp. 1791–1803, 2022.
- [20] B. H. Dr. M. Renukadevi, "Analysis of Alzheimer disease prediction using machine learning techniques," *INFORMATION TECHNOLOGY IN INDUSTRY*, vol. 9, no. 1, pp. 519–525, 2021.