# Brain Fog Consortium Image Analysis Through Internet of Things Using Fog Computing in Stratus Cloud

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***Abstract*—The functioning of human organs is regulated by the central hub of the brain. Brain fog is characterized by a sensation of mental cloudiness. It affects the quality of life, memory impairment, and Alzheimer's disease. Recent investigations have been conducted for the analysis of the brain fog consortium. Brain fog is defined as confusion, diminished mental clarity, forgetfulness, and impaired concentration. Also, it signifies a shortage in nutrients, a sleep disorder, depression, or a thyroid disease. This research proposes the identification of a brain fog consortium utilizing the Internet of Thing (IoT) and fog computing, alongside the suggested stratus cloud system for the brain through IoT integration. It evaluates cognitive impairments, categorizes genuine diseases, and performs analyses using a fog computing platform. The proposed study focuses on investigating segmentation diseases and their excision from the brain's orientational organum, along with prospective detection methodologies within the anatomical structure. The reduction of brain fog can be achieved through the rapid advancement of IoT cloud computing and fog computing services. Experimental results, derived from the data generation of the proposed method, demonstrate efficiency levels in terms of density, affinity ratios, energy consumption, and storage relative to compute time for detecting brain fog. The accuracy of the propagated results is notable, and the implementation within the fog computing gateway is of high qualitative standard.**

***Keywords*—brain consortium, fog computing, Internet of Things (IoT) segmentation, brain fog, brain tumor, IoT detection**

## I. Introduction

The research article discusses how the Internet of Thing (IoT) and fog computing detect and analyze brain fog. Cloud computing plays a crucial role in storing and retrieving data remotely. It keeps the data in the remote server. The brain fog consortium is an informal designation used in scientific and research contexts to denote joint research initiatives aimed at comprehending brain fog and associated cognitive deficits, possibly linked to chronic fatigue syndromes. Researchers from many global universities are increasingly working on extensive studies examining brain fog, particularly in post-infectious diseases such as extended COVID. These research analyses engage interdisciplinary teams utilizing brain imaging, cognitive assessments, and blood biomarkers. The "consortium" for brain fog refers to collaborations or networks of researchers pooling data and methods to advance understanding and task processing, like neuroscience. Brain fog constitutes a collection of symptoms rather than a clinical system response, characterized by difficulties in concentration, memory impairment, mental tiredness, and sluggish cognitive processing. Meteorologists distinguish stratus clouds from fog primarily by altitude: stratus clouds constitute a layer several hundred meters above the ground, whereas fog is a cloud that contacts or originates at the surface. A stratiform cloud type that develops under steady

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atmospheric circumstances and may yield light precipitation.

Cloud computing refers to two types of services: the hardware and system software that provide infrastructure services, and the application services delivered over the internet [1]. Furthermore, services are referred to as SaaS, PaaS, and IaaS to deliver their products. In the cloud, service availability and business continuity involve several steps for data storage, including data confidentiality, addressing data transfer bottlenecks, preventing data lock-in, ensuring scalable storage, and enabling quick scaling, all of which are essential for effective cloud computing. The IoT interacts with cloud computing to exchange data in real-time using embedded sensors such as those found in car lights, thermostats, and refrigerators. The IoT devices have a sensor and minicomputer processors that collect the sensor's data through machine learning. Likewise, fog computing is an architecture that receives the data on a series of nodes in real-time IoT devices [2]. The architecture of cloud computing is centralized and communicates with the devices from a distance. The analysis is long-term, but cloud and fog computing are differentiated. Compared to cloud computing, fog computing is different in its communication, architecture, and so on. Fog computing nodes will send the analytical summary to the cloud [3].

The new description elucidates that fog computing fundamentally varies from cloud computing in architecture, proximity to data sources, and real-time processing capabilities. The proposed architecture utilizes fog nodes for latency-sensitive preliminary healthcare data analysis in proximity to IoT devices, therefore mitigating data transfer bottlenecks, enhancing response time, and improving data confidentiality prior to sending summarized analytical results to the cloud. This hierarchical cloud-fog-IoT architecture for healthcare system response, along with its tailored design and workflow, is explicitly emphasized as the primary innovation of the study, distinctly differentiating it from existing research that depends solely on cloud-centric or generic IoT-fog integrations.

The depiction of the fog includes extensive geographical dispersion, minimal latency, position awareness, a significant quantity of nodes, mobility, the primary function of wireless access, heterogeneity, and a robust presence of streaming and real-time applications [4]. This study defines brain fog as a deficiency in attention and mental clarity, accompanied by forgetfulness and confusion. It is characterized by distraction and fatigue. The sleep disorder and nutritional deficit are the causative factors. The doctor will conduct an X-ray, Magnetic Resonance Imaging (MRI), and Computed Tomography (CT) scans to identify this deficiency. To find the brain fog, the brain has to be viewed and analyzed to see whether the brain fog is affected. For this, the brain fog using fog computing analysis [5] is used. Still, no medications are being used to test brain fog. Still, some of the addresses given by the doctor are to spend much less time on mobile phones and computers, practice positive thinking, reduce stress, improve diet, get enough sleep, exercise, and avoid drugs [6]. One of the ways to find brain fog using brain computing using IoT devices is called direct neural interface, also known as the brain-machine interface. It is done by recording the brainwaves produced by an electroencephalogram. Theodore Berger's experiment records the signal of the brainwaves through the external device known as the Electroencephalographic (EEG) skullcap, which contains 64 electrodes identified through direct communication as well. The device is known as the Brain-Gate Interface (BGI). The consortium analysis is done to determine the brain fog [7]. Also, a Convolutional Neural Network (CNN) in a machine learning algorithm is used to detect the images of the brain and then analyze the disease [8]. It acts as an image recognition model. The traditional technique in the machine learning algorithm for studying the brain image is fog computing for brain fog, brain fog consortium analysis, and stratus cloud for the brain using IoT. Here the results are analyzed to reduce brain fog among humans using different methods and techniques [9]. The primary contribution of the paper:

- The primary contribution of the paper is the analysis of brain fog by the consortium using IoT.
- This research proposed how brain fog is detected and how the brain fog is analyzed and how the cause of the brain fog can be reduced.
- We are implementing the fog computing of brain fog using the consortium analysis technique.
- Brain fog is identified using cloud computing IoT devices to rectify brain fog.

The research includes: Section I discusses the Introduction. In Section II, the related work is stated. Section III proposed an analysis of brain fog using fog computing, and the results and the analysis are done in Section IV. In Section V, the paper is concluded.

## II. Related Work

This research has analyzed some of the articles about IoT and fog computing in the health monitoring process, which helped develop the study; the following are some of the review papers viewed, and a specific investigation was made on the brain fog consortium image using IoT with fog computing against brain fog step-down by the Stratus Cloud.

Klonoff [1] proposed fog and edge computing architectures for managing data from diabetes devices connected to the healthcare IoT. IoT devices include glucose detectors, insulin levels, and other diabetes analysis gadgets. Since fog computing offers more advantages than cloud computing, the researchers opted to use fog computing technology. After a one-minute interval, the IoT device transmits data to a fog node, which then sends it to the cloud for storage and analysis. Servers in various locations will use these sensors and fog computing to virtually store and analyze the data gathered for the diabetes system response. Consequently, the outcome will be sent over the internet. The glucose level in the body will be reported [10]. Kalim *et al.* [10] developed a study on systemic lupus erythematosus, focusing on its impact on quality of life. The primary objective of this literature review is to identify the relationship between cognitive impairment and immunosenescence in Systemic Lupus Erythematosus (SLE). The process of extraction of blood vein for 10–15 cc was done, then the PBMC from the peripheral blood was separated by using the Lymphoprep; the layer formed with the help of PBMC was washed twice with phosphate-buffered saline, and the supernatant was removed. Then, finally, the development of the systemic lupus erythematosus was accelerated to improve the cognitive dysfunction, attention, and the visuospatial domains [11]. Aazam and Huh [11] have proposed IoT devices for sensing and transmitting data with the fog infrastructure for data analysis. Thus, fog computing will help bring the data analysis very close to the sensor. The Raspberry Pi is considered the center node for taking the image from the sensor; in this paper, the testing is done with the damaged lemon, and it is analyzed with the lemon's color difference. The process involved image segmentation, feature extraction, and so on. Hence, the fog nodes contain the different images and the execution time taken for the image processing from the sensor node selected for the estimation process. The delay may have occurred during the image processing for the fog node selection for the data processing method [12].

Singhal *et al*. [13] compared cloud computing and fog computing, which extends cloud computing to the network edge and uses a decentralized computing structure between the cloud and the device to produce data. Fog computing uses cloud data centers for device-end sports, networking, and computing activities. Decentralization and flexibility are the primary differences between cloud and fog computing. Intelligent cities, intelligent network transport, real-time analysis, and other uses of fog computing are listed below [14]. Cheikhrouhou *et al*. [12] developed the one-dimensional CNN approach for fog-cloud ECG arrhythmia analysis. Cardiovascular illness is the leading cause of mortality, and ECG readings and IoT devices may identify irregular pulse rates. Fog computing is as powerful as edge computing but less powerful than cloud computing. The fog-based gateways link with wearable devices for reduced latency and better service. Using the arrhythmia databases and the grid search technique, the proposed solution increase's reaction time by 25% [15].

With the use of IoT devices and fog computing, Dev and Malik [16], created a monitoring and prediction system for stroke illness. Most simulation users are in catastrophic condition due to healthcare personnel's ignorance of the physiological features of strokes. Simulation users take longer to recover. Diagnostic technologies and image processing are increasing daily in the Healthcare industry. This study develops a stroke monitoring system using wearable IoT devices and fog computing. The proposed method for predicting and monitoring stroke simulation users is linked to the ensemble classifier. Data for the process comes from many sources. The output will be assessed using accuracy, specificity, and sensitivity [17].

Feng *et al*. [18] examined the industrial Cyber-Physical-Social Systems (CPSSs) paradigm in the context of cloud-fog computing and its implications for industrial data processing. They developed High-Order Bi-Lanczos (HOBI-Lanczos) for the examination of heterogeneous data. They facilitate the processing of industrial data applications through cloud-fog computing, enabling secure execution of industrial data analysis in both fog and cloud environments. This model inspires us to implement privacy preservation through a brain-controlled case study. Empirical evidence has demonstrated the security of the proposed method [19].

Jiang *et al*. [20] examined the hierarchical cooperative caching issue in fog networks that provide radio access (F-RANs). They examined the hierarchical cooperative caching optimization problem to reduce delay. They establish vertical collaboration between the cloud server and Fog-Access Points (F-APs) by utilizing Brainstorm Optimization (BSO). The Genetic Algorithm (GA) enhances the initialization efficacy of the BSO method in conjunction with Opposition-Based Learning (OBL) concerning the solution space. The analytical results of objective space through individual classification provide insights into global convergence [21].

Liang *et al*. [22] examined abnormal brain regions in Parkinson's disease simulation users exhibiting a freezing gait. They examined EEG data from simulation users with healthy controls. They extracted specific brain areas to assess power density and connectivity. The graph theory examines brain changes between FoG simulation users and HCs based on the clustering coefficient, degree, global efficiency, and nodal efficiency. The researchers examined the FoG simulation users about diminished connectivity in the bilateral frontal-mid, Supplementary Motor Area (SMA), postcentral, and precentral regions. This analysis provides the most substantial correlations identified among the FoG simulation users [11].

Zhu *et al.* [23] highlighted that the substantial volume of EEG data used to validate Brain-Computer Interface (BCI) systems poses issues within the Internet of Things (IoT). They present an innovative multichannel asymmetrical variational Discrete Cosine Transform (DCT) network for the compression of EEG data utilizing an edge-fog computing framework. They employed parallel trainable hard-thresholding and scaling operators for the management of duplicate data. Fog layer employs the inverse DCT for reconstructing multi-head attention, which is utilized in adaptive filtering at fog levels. This research formulates a new variational inference to minimize the loss function relative to accuracy [24].

Arenas-Deseano *et al*. [25] present a robust multiplatform Artificial Intelligence (AI) system for emotion classification. They created an initial-phase AI model within a heterogeneous hardware ecosystem utilizing a real-time service robot, leveraging cloud connection and fog computing. CNNs utilizing TensorFlow do emotion classification in various emotional states. Fog computing improves latency and reaction time in real-time applications. A comparative analysis was performed utilizing Raspberry Pi-4 for monitoring and sensor data collection. The performance's outcome precisely categorizes various emotional states. The categorization alert systems utilize human-machine interface frameworks in AI-driven service robots [26].

## III. Proposed Analysis of Brain Fog Using Fog Computing

As cloud computing provides different services to manage the data, like data storing, networking, and so on, fog computing is the architecture for faster computing of the data that is received from IoT devices or sensors through a series of nodes. Data from various IoT devices and sensors are utilized for analysis in day-to-day life. It will continuously generate enormous amounts of data to manage this data. These methods of computing technologies, like cloud, fog, and edge computing, were used [27]. Slow responses will not suit any system requiring an immediate response to the upcoming process; thus, fog computing has been introduced to avoid the cloud's slow response, reduce the cloud's latency, and increase privacy and security. The fog node will be present near the data generation area. Sensors and IoT devices provide data to the fog server first. The fog server analyzes data, determines the most needed data, and transmits it to the cloud server for processing and quicker response. Fog computing is the next step of cloud computing or the layer between clouds and edge devices.

The fog computing method is used for brain fog detection. It is a temporary problem, but it will lead to various serious hazards. It is caused by continuous invasion of electronic radiations faced by the human brain, work and family stress, lack of sleep due to workload for an extended period, continuous mobile and system usage, nutrient deficiency, thyroid imbalance, discontinuous and lack of timely food habits, hormonal imbalance, vitamin and mineral deficiencies in the body, and diseases like multiple sclerosis, Parkinson's, and celiac, and in some cases invasion of harmful viruses and bacteria like COVID-19 will lead to brain fog, which is the swollen brain [28].

Brain fog will lead to insomnia, confusion, low energy in the body, frequent tiredness, always being in a sad and anxious mood, headaches, forgetting things quickly and being unable to recover them, feeling cloudy-brained, and sometimes even memory loss. To overcome brain fog, available medications like L-carnitine L-tartrate are used to treat the lack of vitamins C, A, E, and B complex and maybe other causes of brain fog; hence, calcium ascorbate, acetate, and DL-alpha-tocopheryl acetate are taken as supplements by the simulation user to treat brain fog. These medications will give a temporary solution to brain fog [25]. To get a permanent solution and immediate reduction result, a fog computing way of retrieving technique has been used to treat brain fog. In some cases, it won't work, as in the case of the second image. The invasion of COVID-19 led to a number of causes of brain fog. It continues even after the disease is cured. Brain fog can even lead to suicide [23].

Fig. 1 represents the application for brain fog using fog computing, as brain fog is a temporary disease that is caused by stress and can be cured by simple methods like meditation and so on [22]. Simulation users affected by brain fog need assistance to recover. Hence, the simulation user will request help through some intermediate devices, and the cloud computing layer will understand the problem. Then the recovery solution will be provided by the fog computing layer after processing the problem [29]. The following Algorithm 1 elaborates on how cloud computing is applied to fog computing to make an efficient brain fog analysis [16].

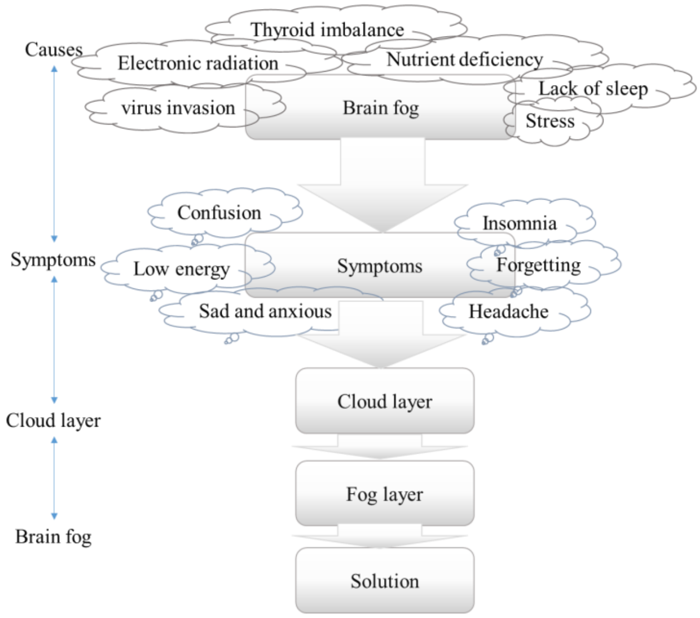


Fig. 1. Application of fog computing in brain fog.

### *A. Algorithm for Fog Computing Uses Cloud Computing*

For the task in the cloud (which is mentioned in the Algorithm 1), the count of ants aimed at or taken is less than the count of functions. All the tasks started with resources and an initial task for processing, then the task was executed by the following,

$$\frac{\left(\pi_{jk}\right)^{\alpha}\left(\eta_{jk}\right)^{\beta}}{\sum allowed\left(\pi_{ji}\right)^{\alpha}\left(\eta_{ji}\right)^{\beta}} \tag{1}$$

where $\pi_{jk}$ describes the pheromone value that is associated with the job and the resource. $\eta_{jk}$ refers to the function. The $\alpha$ determines the influence of pheromone value $\beta$-determines the influence of the function.

**Algorithm 1: The Algorithm for Fog Computing Uses Cloud Computing to Receive a Last Resulting Data**

```
Initialization;
    Initialize the path, initial solution=0, samples n, node information,
overload
Output;
    Implementation of Offloading node and recently received result
data;
Compute the solution:
    For (do→ all data)
        If (choose next resource),
            Calculate transition rule from Eq. (1),
        Else
Select the previous solution,
    End for,
  Until constructs the solution,
  Fitness: compute → the solution of each record
Replacement:
    If (fitness of solution > optimal solution)
        Replace the recorded data
        Otherwise, go to step 18
 Update the local pheromone and global pheromone.
Repeat steps 2 to 6 until the condition is satisfied.
An optimal solution to the result data is found.
 T← find Topography ();
A← find Approachable Nodes ();
 i← find Most beneficial Node (A, T);
while (i prepare for receiving result) do
send Planning Request ();
 P← find Path (α, β);
SO← get OF Switch Path(P);
for (switch s in S) do
apply Flow Rules Path ();
 end
 end
 return i
```

Each creates the outcome of assigning tasks to resources. Start with a positive pheromone value and modify it at the conclusion of the loop [18]. The optimum solution for that iteration is the one that minimizes or maximizes the goal function. Iterations' most helpful solution is the ultimate optimum solution [20].

The aim and operation of the targeted offloading service for a fog computing system are discussed. The request is sent to the orchestrator when the node is overloaded. The request consists of the information features of QoS. Offloading services are called when the request is received, which provides the current status of nodes in the system. Based upon this, the path selection of filtering the node can afford the request and ranking the node [13]. The first step is to locate the Topography() function. After asserting all requisites, the findApproachableNodes() function returns a list of executable nodes [30]. The second step, which is done by the findMostBeneficialNode() function, ranks the executable. To enforce this approach path, the algorithm first computes the individual marks of each request and then finally finds the path to transmit the result.

### *B. Image Analysis for Brain Fog*

The brain fog will cause brain enlargement. Thus, it is analyzed through the ECG captured brain image at the time of meditation, taking enough sleep, and so on. The images are captured from the ECG sensor, which is fitted into the IoT devices. Thus, the image captured will be processed to identify brain fog. Before processing, the image noise in the data needs to be removed using a Gaussian filter, and then the processing will be done by comparing the images.

Fig. 2 show the reduction of brain fog by applying fog computing techniques compared to standard medication. The brain image was captured through EEG techniques for understanding the brain fog noise from the image, which is removed in a pre-processing method, and then the image processing takes place. The first image represents a swollen brain, denoted as brain fog. The second image represents the failure of standard medications, and the brain fog is still being detected. The third image represents a reduction in swelling after applying the fog computing technique to treat brain fog. Before getting into task processing methodology using fog computing, we must learn how fog computing retrieves the data faster with less latency.

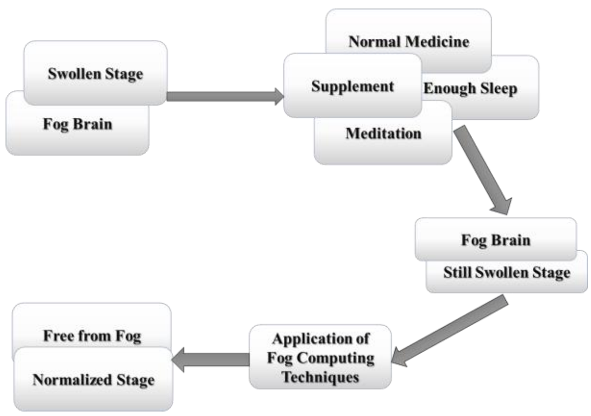


Fig. 2. Brain fog clinical image verification.

### C. Behavioral Analysis of Simulation Users Using IOT Sensors

The people affected by brain fog will behave abnormally in some conditions, and their mood will always be upset. They feel very anxious, tense, stressed, and frustrated. These persistent mental illnesses will lead to suicide in some severe cases. To control the risk of brain fog, continuous monitoring is required. Hence, analyzing the behavior and monitoring the simulation users using IoT. Therefore, wireless sensors have been set to monitor the simulation user and provide continued guidance to follow healthy habits. The heart and brain are like magical connectors. Any thought that rises in your brain will directly affect the heart and the entire system. When the person feels stressed or frustrated, their heart rate will increase abnormally. To monitor the pumping rate a wireless ECG sensor has been used. Similarly, the blood pressure of the simulation user will increase and decrease unevenly. To monitor the blood pressure, a wireless blood pressure sensor is used. Blood pressure and frustration will lead to an increase in body temperature. Hence, a temperature sensor is attached. To monitor the location of the person, a motion sensor has been used. The EEG sensor plays a vital role in analyzing the behavior of the simulation user. Three nodes are given input from the human brain to open the BCI PCB (sensor board). The positive and negative electrode nodes are given information to the ADS1299 IC. The bias electrode node is given as input to the bias driver. A 6 nA current is provided to the IC. Output from the IC is given to the ADC converter.

Moreover, with prompt dietary instructions, artificial doctors are connected and directed via mobile phones; this assists the simulation user in adhering to their diet, maintaining good eating habits, timely medicine consumption, and regular exercise. In addition to this sensor, smoke sensors, alcohol sensors, and several others may be included to promote good habits. This system enables the simulation user's family and friends to remotely monitor the simulation user's behavior via fog computing. All sensors are interconnected via IoT, and the output is shown on mobile devices. Acquired data is stored on the cloud server. Subsequent to the cloud server, it is sent to the fog node. Fog nodes are linked via the F2F network.

Fog computing offers diminished latency, better reaction times, enhanced compliance, heightened security, higher data privacy, lower bandwidth expenses, overall speed and efficiency, and less dependence on WAN services compared to cloud computing services. Fog retrieves the most sought-after data from the cloud server and transmits it to the closest server. This helps the simulation user's relatives and friends to gather information about him from anywhere through IoT devices. The brain fog consortium analysis was made on more than 200 simulation users and obtained an accurate result. More than 180 simulation users who had been treated with the fog computing approach emerged from brain fog as a result of the experiment. Fog computing facilitates the rapid retrieval of critical simulation user status data. The following technique describes in detail the effective usage of fog computing for brain fog consortium analysis.

### D. Algorithm for Fog Computing for Brain Fog Consortium Analysis

Brain fog can be caused by a lack of sleep and stress and mainly manifests as forgetfulness, inability to focus, and uncertain. First, we analyze the brain fog of consortium people by the clustering methodology, and then we reduce the count of people affected by the brain fog syndrome. Here, by following these steps, Algorithm 2 can compute the brain fog consortium of people.

**Algorithm 2: Algorithm of Fog Computing for Brain fog Consortium Analysis**

```
INPUT;
Consortium population, individual, consortium
OUTPUT;
Analyze brain fog of consortium peoples
WHILE stop condition () Do
        FOR (G = 1 to G_n peoples) Do
                FOR (j = 1 to N_i individuals) Do
              Evaluate brain fog of individuals;
                  fppl = f(X_j)
                  If fppl > p affected, then
                  P affected = fppl
                  P_j–X_j
                END FOR
```

$$Gbf = \left\{ G \middle| f(p_j) = \max(f(px_i), C \in N(X_j)) \right\};$$

```
          Update consortium peoples (fppl);
          Cross over create new individual of consortium peoples;
           Mutate the created new individuals from the consortium
people;
           Assorting the new individuals to peoples G+1;
        END FOR
END WHILE
RETURN analyze brain fog of consortium peoples
```

The cognitive analysis process of the brain fog consortium analysis is employed for analyzing the brain fog of individuals in a consortium of people (fog peoples (fppl)). Initially, the first individual in the consortium of people has some inability to focus, confusion, lack of sleep, and stress. It is detected, and the individual is separated, and then another individual in the consortium of people checks if they have symptoms of brain fog. If it is true, then the individual is separated, and similarly, the process is continued till the end of the individual in the consortium of people. Then the separated individuals are taken into another process of reducing the brain fog. Before this, the process of crossover and mutation is performed.

Fig. 3 illustrates IoT sensors identifying brain fog in the simulation user's behavior. Since brain fog raises the simulation user's average body temperature and pressure, heart rate, temperature, blood pressure, and EEG sensors were employed. Internet-connected mobile apps gather data, which is sent to the cloud and kept on the server. Comparison of relevant data will speed up data processing for the fog layer to determine brain fog in the simulation user. Finally, the simulation user will get counsel based on the results. The following method explains fog computing analysis for brain fog removal.

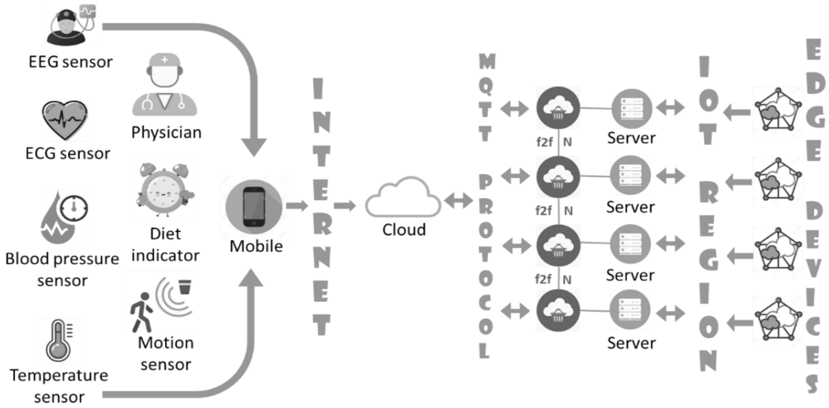


Fig. 3. Brain fog analysis using IoT.

*1) Algorithm for fog computing for brain fog reduction*

In fog computing, to reduce brain fog, first compute the maximum, minimum, and mean values of brain fog symptoms based on Algorithm 3. The Elbow method is used for calculating the cluster centroid.

**Algorithm 3: Algorithm for Fog Computing for Brain Fog Reduction**

**Input**:
time-triggered Brain fog symptoms, which include
BFS=x;
Counter= changes in mental health;
Where, x = (lack of sleep, thoughtfulness);
Y= time-triggered;
**Output**:
Efficient Data reduction of brain fog symptoms.
**For** each (time-triggered → newly accessible resources) do
switch to initial inputs
**End**;
Perform the calculation for maximum, minimum, and mean values for brain fog symptoms
Elbow method used for calculating the cluster centroid,

$$K = \sum_{i=1}^{n} \sum_{x \in C} \left| x_{bfc} - m_{bfc} \right|^2$$

**Repeat**
The initial cluster centroids are selected from BFS here, Cbfs=6;
The mean value Mbfs of each data is reallocated on its similarities, and then the mean value is recalculated as Mbfs*.
Find all symptoms threshold
**Until**;
Short-term data storage is counter ++

Energy required for transmission,
$E = E_{WF} + E_{WF}$
Calculating the $E_{WF}$ and $E_{WF}$,
Compute $E_{WF} = E_{WMF} + E_{WEF} + E_{ZFC} + E_{WEC} + E_{ZCF} + E_{TFM}$
Compute $E_{WF} = E_{WMC} + E_{WEC} + E_{TCM}$
**If** (counter=limit of time-triggered)
**Throughput** = Extract the relevant data from each resource
**Else**;
Move to the initial stage and set counter=0
Check the outliers of the computing
**For** each (outliers found) **do**
**Throughput** = initial stage
**end**;
**Include find**: next_ possibility = throughput (outliers found||extract relevant symptoms from resources)
**return** efficient data reduction of fog symptoms

$$K = \sum_{i=1}^{n} \sum_{x \in C} \left| x_{bfs} - m_{bfs} \right| \tag{2}$$

where $n$ is the number of clusters, which is a group of the same symptoms, $C$-number of cases that are a variety of symptoms, $x_{bfs}$ is the first individual to have symptoms of brain fog and the $m_{bfs}$ is the centroid of each group.

*2) Energy requirements*

Energy requirements also have many phases, and the energy requirement depends on fog computing. The description for the phases as follows Table I.

TABLE I. PARAMETER DESCRIPTION FOR VARIABLE FOG COMPUTING FOR BRAIN FOG REDUCTION ALGORITHM

| $E_{WMF}$ | Description for Variable |
|---|---|
| $E_{WE}$ | Energy needs for transporting all tasks to the fog node. |
| $E_{ZFC}$ | Energy is required to complete the tasks by fog node. |
| $E_{WEC}$ | The fog node requires energy to do such tasks. |
| $E_{ZCF}$ | Energy requirements for further processing of the jobs in the cloud center. |
| $E_{TFM}$ | The cloud centers need energy to perform such tasks. |
| $E_{WEC}$ | Transferring the result from the fog node to the device requires energy after processing. |
| $E_{WMC}$ | The energy needs of the process are fully handled by the cloud center. |
| $E_{TCM}$ | Energy needs for transferring tasks to cloud centers. |

The initial brain fog-affected individual is considered, and enough time to recover from the peculiar symptom is examined. The clustering technique is tucked into several entities of symptoms and assesses the effectiveness of each symptom in the whole individual consortium. Energy is crucial to performing computing. This theory is employed based on the energy and time, during which the brain fog symptoms may change. Each outlier found, which means the reduction of symptoms of individuals, is found.

Brain stimulation is the process of understanding the complete contribution of the brain, which will help treat and diagnose brain diseases. In the task processing of brain fog, the simulated brain in the fog computing technology will help provide a better result. The process of analysis using fog computing will provide a faster response to the cloud, reduce the latency of the cloud, and increase privacy and security. Thus, to increase the process of analyzing the data, brain-simulated nodes will be very helpful, as they contain the complete structure and contribution of the brain. The process of analyzing brain fog will be much faster than the normal computing method. Hence, the solution will be gained faster, the method of diagnosing the disease will also be in the faster range, and so the risk of brain fog will be reduced in the faster range.

Fig. 4 provides the process of analyzing the problem to provide a solution for it using the brain nodes. The data are collected from the memory, and then the brain node memory will analyze the data and find the problem; after finding the problem memory, the brain node will process and analyze it to provide a solution for the problem. The following Algorithm produces the resulting gateway for brain fog and fog computing.

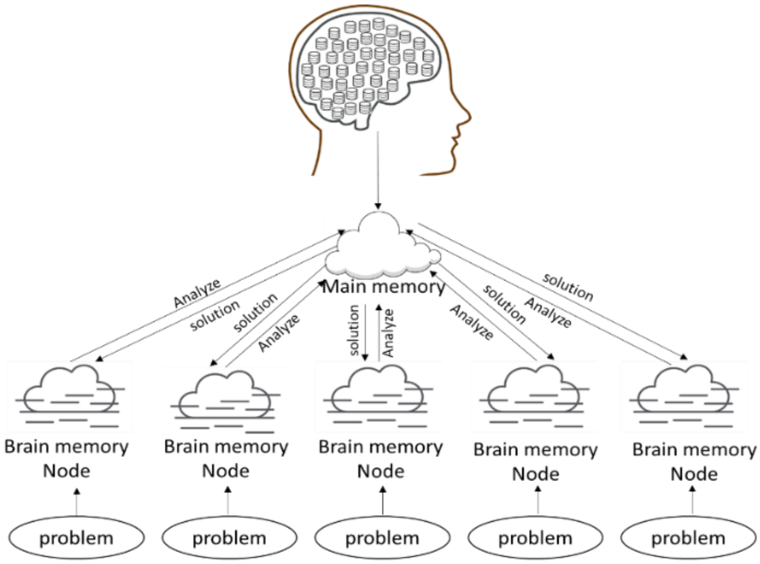


Fig. 4. Process of problem analysis and solution based on brain nod.

### 3) *Algorithm for the result gateway for brain fog and fog computing*

To obtain the resulting gateway for brain fog via the use of fog computing, we have proposed a device for fog and cloud data transfer technique.

Performance time is classified into many forms, which are listed in Table II.

TABLE II. PARAMETER DESCRIPTION FOR VARIABLE RESULT GATEWAY FOR BRAIN FOG COMPUTING ALGORITHM

| Variable | Description for variable |
|---|---|
| $T_{BT}$ | Decision-making is based on the requirement, which path is suitable, and whether the fog node is processing or not. It is the more crucial stage of decision-making. |
| $T_{WDF}$ | Requisite of time to transfer the chores from device to fog node. |
| $T_{WCF}$ | Requisite of time for processing such chores by the fog node. |
| $T_{SFC}$ | Requisite time to transfer the chores from the fog node to the cloud center. |
| $T_{TEC}$ | Requisite of time for processing such chores by the cloud centers. |
| $T_{BFD}$ | After processing, the result of the brain fog is transferred to the fog node. |
| $T_{ACD}$ | After processing, the result of the brain fog is transferred to the device node. |
| $T_{WDC}$ | Requisite of time to transfer the chores from device to cloud centers. |
| $T_{ED}$ | Time is taken for performing the chores by the device itself. |

Brain fog computing results are based on the above cognitive process. This is typically employed to examine whether it is beneficial to offload the chores or not. But the factors only decide whether the chores will be offloaded or not. These are performance time, energy requisites, and so on. In that case, we compute the value of factors in the abovementioned cases, which are given in steps five, six, seven, and eight. Based on this decision-making process, a required and efficient gateway for transferring and finding the results from fog and cloud centers is needed. The resultant gateway decision-making is updated and entirely relies on the user.

The suggested fog computing-based framework for brain fog analysis was validated via an extensive simulation-driven assessment concentrating on the accuracy, efficiency, and adaptability of the algorithms. The fog-cloud offloading optimization algorithm was evaluated by contrasting its latency, resource consumption, and task completion time with cloud-only and fog-only baselines, revealing enhanced load balancing and diminished response time. The collaborative analysis methodology was evaluated with population-level brain fog datasets, demonstrating superior classification accuracy and expedited convergence compared to conventional aggregation methods. The data reduction method was assessed on time-triggered symptom streams, demonstrating efficient data transmission reduction while maintaining essential symptom patterns and decreasing energy usage. The resulting gateway decision method was ultimately evaluated under diverse network and processing settings, demonstrating precise and adaptive fog-cloud execution decisions, enhanced throughput, and reduced deadline miss percentages. Multiple studies utilizing statistical analysis validated the robustness and reproducibility of the proposed framework.

For treating brain fog, the notion of fog computing is used in the therapy approach. A person who is experiencing brain fog will have difficulty responding to inquiries in a timely manner, will have memory loss, will be unable to think properly, and will be in a state of confusion. Using the fog computing approach, it is possible to find a solution to these state-of-the-brain challenges. When there is *n* numbers of data saved in the cloud, it takes some time to process the specific data that is needed at the moment. This causes the cloud server to experience a sort of stress. Because of this, cloud computing has a slower reaction time when dealing with a multitude of data. Similarly, the brain faces the same problem when dealing with a large memory with unwanted and wanted data. The purpose of the fog is to analyze the information and gather the information that is required at present. Its fast response is because it is available very near to the edge device, and also because it does not carry bulk data as a cloud. Similarly, we have to stimulate the brain memory nodes, which contain the recent information that is stored. Stimulation of brain nodes will help to analyze the recent information required. After finding the particular information required, the neural system helps to gather the specific information from the main memory. Continuous stimulation processes and medication task processing, along with diet, help to come out of brain fog. This is examined using n simulation users affected by brain fog, yielding practical results in clinical and behavioral outputs with respect to Algorithm 4.

**Algorithm 4: Algorithm for Result Gateway for Brain Fog Computing**

1. INPUT ARGUMENTS; $T_{BT}$, $T_{WDF}$, $T_{WCF}$, $T_{SFC}$, $T_{TEC}$, $T_{ACF}$, $T_{BFD}$, $T_{ACD}$, $T_{WDC}$, $T_{ED}$.
2. OUTPUT; loading decision
3. PROCESS: $T_{BT}$, $T_{WDF}$, and so on.
4. Examine
   results of the brain fog can be executed on the local fog node too.
   Compute $T_{WF} = T_{BT}, + T_{WDF} + T_{WCF} + T_{SFC} + T_{TEC} + T_{ACF} + T_{BFD}$
   Compute $T_{WC} = T_{BT} + T_{WDC} + T_{EC} + T_{CM}$
   Compare $T_{ED}$ with $T_{WF}$ and $T_{WC}$.
5. CHECK case1;
   5.1 If $T_{ED} > T_{WF}$ and $T_{ED} < T_{WC}$,
   5.2 Results of the brain fog will be uploaded to the fog node
   5.3Otherwise, go to step 6
6. case2;
   6.1 If $T_{ED} > T_{WF}$ and $T_{ED} > T_{WC}$
   6.2 check if $T_{WF} > T_{WC}$. If yes result of the brain fog will be uploaded to the cloud data center; otherwise, to the fog node
   6.3 Otherwise, go to step 7
7. case3;
   7.1 If $T_{ED} < T_{WF}$ and $T_{ED} > T_{WC}$,
   7.2 The result of the brain fog will be uploaded to the cloud data center
   7.3Otherwise, go to step 8
8. case4;
   8.1 If $T_{ED} \leq T_{WF}$ and $T_{ED} \leq T_{WC}$,
   8.2 The result of the brain fog is in data center
   8.3 repeat steps 5–8
   8.4 Otherwise, go to step 9
9. RESULT; based on the decision-making, the processing gateway is founded.
10. UPDATE; the result of the brain fog selection path
    Fac = factor chosen by the user
    Factor decrease = 0.1
    Information of brain fog analysis may increment
11. END UPDATE

## IV. Result Analysis and Discussion

All simulation datasets were manipulated to simulate real-time IoT healthcare scenarios. No human subjects or simulation user data were used in the simulation-based experiments, assuring ethical compliance and thorough performance evaluation.

### *A. Datasets with Simulation User Trials*

Fog-cloud simulation datasets were used to evaluate the IoT-fog-cloud architecture without simulation user trials. Fog-based healthcare data processing performance can be tested, replicated, and evaluated with these datasets.

iFogSim Simulation Data: The iFogSim toolbox generated simulated IoT data streams and fog computing workloads.

The IoT layer simulated healthcare imaging and physiological sensor data, while fog nodes pre-processed and summarized latency sensitively. End-to-end latency, network utilization, energy consumption, and task execution time were measured. The datasets simulate heterogeneous fog nodes, changeable network circumstances, and dynamic IoT traffic. The proposed stratus cloud environment was tested for load balancing, job scheduling efficiency, and cloud offloading using the generated datasets.

In fog computing, test internet of things technologies. A high-to-medium cross-industry framework, OpenFog helps software developers and system architects build the first open fog nodes and networks. An interoperable, tested collection of hardware and software standards will unify fog computing for brain fog reduction under OpenFog. A decentralized computing framework connects the IoT with data-producing devices. Machine learning's convolutional neural network analyzes brain pictures. This study analyzes brain fog consortiums, improves the creator module, and calculates energy consumption for density, affinity ratio, security, storage, and network latency, which is 85% effective.

$$E\left(Energy\ Consumption\right) = power\ unit \times \frac{time_{Brain\ fog\ cell}}{1000} \quad (3)$$

Where "*E*" represents "energy consumption", "*p*" represents "power unit" and "*t*" represents "time".

Table III shows fog consortium energy consumption for urban density based on brain fog cell rise and decrease, cloud, fog consortium power unit, brain fog cell duration, and energy consumption output. Brain fog cells fall by 12%.

Eq. (3) explicitly demonstrates that energy consumption escalates linearly with both the processing length of brain fog cells and the power utilization of the fog consortium, consistent with the reported outcomes amid rising urban density. With rising urban density, the quantity of active brain fog cells escalates, resulting in heightened power consumption of fog nodes and extended processing times, hence yielding moderate energy consumption values between 0.006 and 0.016 units. In areas of high urban density, when extensive brain fog analysis is necessary, energy consumption dramatically increases, peaking at around 0.059 units. Notwithstanding this augmentation, the fog consortium upholds energy efficiency by locally processing data and minimizing superfluous cloud connectivity. Table III inference result first-level range is 12.4–34. Range 0.0064 increases lower-level accuracy, while 39 to 59.4 is second-level. Lower accuracy increases by 0.0261. The third level is 66.4–88. Range 0.059 increases the accuracy.

TABLE III. ENERGY CONSUMPTION FOR URBAN DENSITY-BASED ON BRAIN FOG CELLS

| Brain Fog Cells Increase | | Brain Fog Cell Decreases | | Cloud | | Power Unit for Fog Consortium | Brain Fog Cell Time | Energy Consumption |
|---|---|---|---|---|---|---|---|---|
| X (Urban Density) | Y (Fog Consortium Energy Consumption) | X (Urban Density) | X (Urban Density) | Y (Fog Consortium Energy Consumption) | X (Urban Density) | | | |
| 12.4 | 5.5 | 15.78 | 7.8 | 20 | 12.6 | 0.45 | 0.5 | 0.000225 |
| 5.6 | 10.5 | 23.56 | 20.56 | 56.8 | 56.8 | 0.98 | 1 | 0.00098 |
| 23.2 | 19.5 | 35.42 | 27.8 | 51.4 | 25.8 | 1.51 | 1.5 | 0.0022 |
| 15.78 | 25.89 | 45.24 | 56.7 | 72.4 | 56.78 | 2.04 | 2 | 0.00408 |
| 34 | 33.5 | 87.9 | 47.8 | 82.8 | 39 | 2.57 | 2.5 | 0.0064 |
| 39 | 40.5 | 64.88 | 32.7 | 78.8 | 45.6 | 3.1 | 3 | 0.0093 |
| 44.8 | 30.5 | 74.7 | 67.8 | 114.2 | 69.45 | 3.63 | 3.5 | 0.012 |
| 51.6 | 54.5 | 84.52 | 95.6 | 134.7 | 58.8 | 4.16 | 4 | 0.01664 |
| 55.6 | 61.5 | 56.8 | 87.8 | 145.6 | 65.4 | 4.69 | 4.5 | 0.021 |
| 59.4 | 78.9 | 104.16 | 112.4 | 198.6 | 98.4 | 5.22 | 5 | 0.0261 |
| 66.4 | 75.5 | 98.7 | 107.8 | 177 | 78.6 | 5.75 | 5.5 | 0.031 |
| 68.67 | 82.5 | 123.8 | 123.78 | 192.7 | 67.8 | 6.28 | 6 | 0.0376 |
| 77.2 | 56.8 | 78 | 156.7 | 78.5 | 91.8 | 6.81 | 6.5 | 0.044 |
| 70 | 96.5 | 143.44 | 137.8 | 224.1 | 78.9 | 7.34 | 7 | 0.0513 |
| 88 | 103.5 | 153.26 | 147.8 | 239.8 | 105 | 7.87 | 7.5 | 0.05902 |

Fig. 5 quantitatively illustrates that the energy expenditure per output of brain fog cells diminishes by around 12%. As urban density diminishes, the spatial density of brain fog cells increases, leading to heightened energy consumption, which is calculated by multiplying each load by its operational hours.

Table IV shows energy consumption for affinity ratio brain fog cells based on increased, decreased, cloud, power unit, time, and energy consumption output. Brain fog cells decreased by about 12%. In Table IV, the inference result shows that low-level accuracy increases by 0.231 for the first level, 0.098 for the second, and 0.558 for the third. Table IV illustrates a distinct correlation between the affinity ratio of brain fog cells and the energy consumption of the fog consortium, as determined by the Eq. (3). At diminished affinity ratios, both the power unit and cognitive processing duration exhibit minimal values, leading to exceedingly low energy consumption metrics (e.g., 0.00063 units for $p$ = 1.26 and $t$ = 0.5 ms). As the affinity ratio escalates, the computational burden on fog nodes intensifies, resulting in elevated power consumption and extended processing durations, hence proportionately augmenting energy usage. Moderate affinity ratios produce energy values between 0.01 and 0.10 units, signifying feasible fog resource usage. At elevated affinity ratios, where comprehensive brain fog investigation is necessitated, energy expenditure markedly escalates, peaking at roughly 0.601 units.

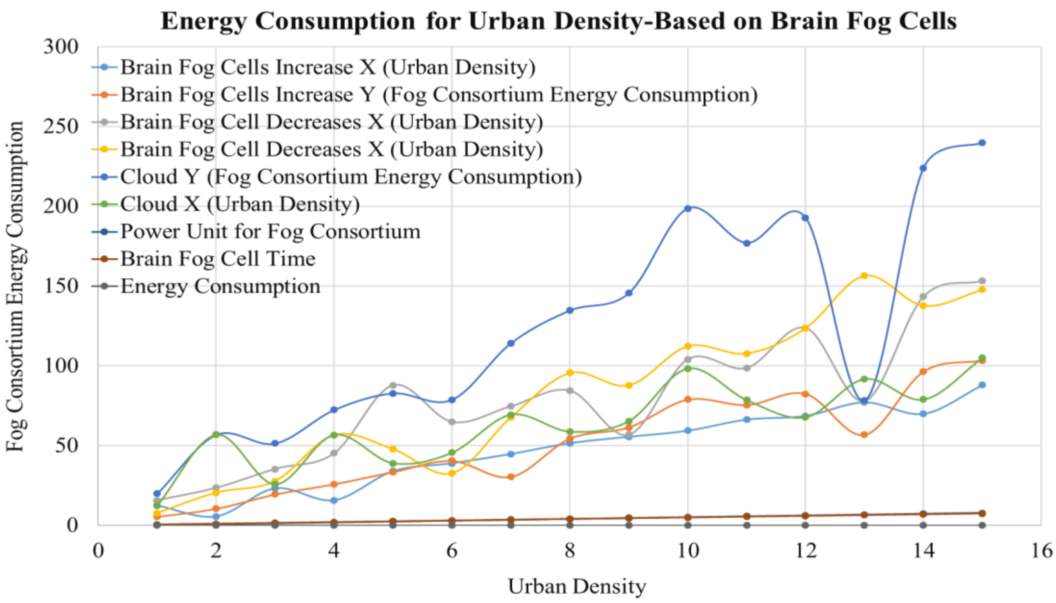


Fig. 5. Urban density for fog consortium energy consumption.

TABLE IV. ENERGY CONSUMPTION FOR AFFINITY RATIO BASED ON BRAIN FOG CELLS

| The affinity ratio of brain fog cells increased | The affinity ratio of brain fog cells decreased | Affinity ratio cloud | Power unit for affinity ratio | Brain fog cell time | Energy consumption |
|---|---|---|---|---|---|
| 2.35 | 1.08 | 0.78 | 1.26 | 0.5 | 0.00063 |
| 23.67 | 5.89 | 6.89 | 15.9 | 1 | 0.0159 |
| 12.99 | 19.7 | 23.98 | 3.14 | 1.5 | 0.0047 |
| 18.31 | 15.51 | 19.11 | 24.08 | 2 | 0.048 |
| 29.63 | 20.32 | 25.22 | 5.02 | 2.5 | 0.012 |
| 18.95 | 5.13 | 41.33 | 35.96 | 3 | 0.10 |
| 34.27 | 29.94 | 37.44 | 61.9 | 3.5 | 0.216 |
| 29.59 | 54.75 | 43.55 | 57.84 | 4 | 0.231 |
| 44.91 | 39.56 | 69.66 | 83.78 | 4.5 | 0.37 |
| 35.23 | 64.37 | 55.77 | 19.72 | 5 | 0.098 |
| 55.55 | 49.18 | 41.88 | 71.66 | 5.5 | 0.394 |
| 80.87 | 33.99 | 67.99 | 11.6 | 6 | 0.0696 |
| 66.19 | 58.8 | 94.1 | 92.54 | 6.5 | 0.601 |
| 71.51 | 83.61 | 80.21 | 13.48 | 7 | 0.094 |
| 96.83 | 98.42 | 86.32 | 74.42 | 7.5 | 0.558 |

Fig. 6 describes an affinity ratio of the competitive interactions among a tumor, target, and unmodified brain fog cells, which was an essential factor for the performance.

$$Risk\ insecurity = fog\ consortium\ data \times security\ concern\ value \quad (4)$$

Risk insecurity involves recognizing and addressing security concerns. Based on fog consortium data and security concerns, Table V predicts a 35% security risk. This table inference result shows that lower level accuracy increases by 4017.4 from 12.4 to 34 and by 13,853.7 from 39.4 to 61. The third level is 66.4–88. Improves lower accuracy by 26,936.8.

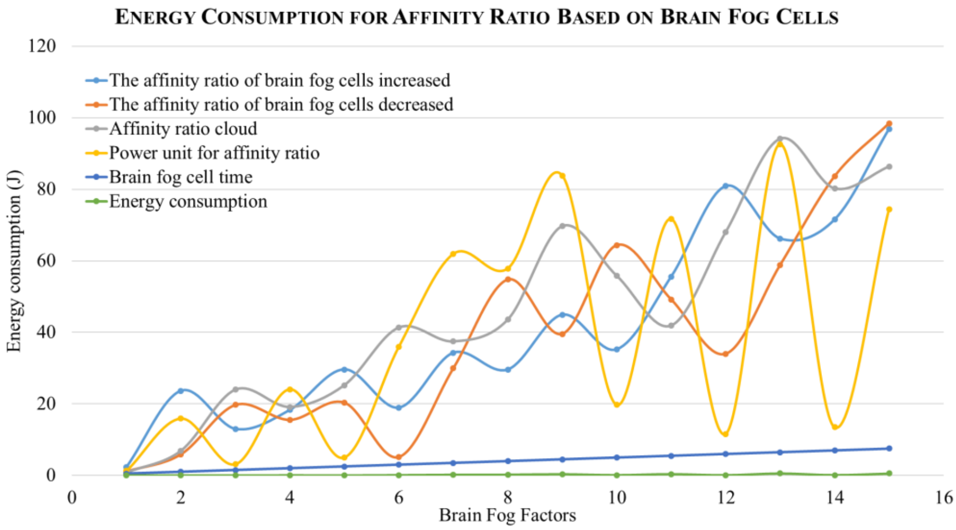


Fig. 6. Affinity ratio brain fog cell energy consumption.

TABLE V. SECURITY CONCERN FOR FOG CONSORTIUM DATA

| Fog consortium data (count) | Security concern | | | | | Security Concern Value (Risk Index) | Risk in Security (Risk Score) |
|---|---|---|---|---|---|---|---|
| | Complexity-Computational Time (ms) | Security (Bits of Security) | Authentication Time (ms) | Maintenance (hours/month) | Power Consumption (Joules (J)) | | |
| 12.4 | 7.8 | 3.56 | 12.6 | 5.78 | 1.26 | 31 | 384.4 |
| 17.8 | 17.8 | 5.7 | 19.2 | 7.89 | 2.2 | 52.79 | 939.6 |
| 23.2 | 27.8 | 7.84 | 25.8 | 10 | 3.14 | 74.58 | 1730.2 |
| 28.6 | 37.8 | 9.98 | 32.4 | 12.11 | 4.08 | 96.37 | 2756.1 |
| 34 | 47.8 | 12.12 | 39 | 14.22 | 5.02 | 118.16 | 4017.44 |
| 39.4 | 57.8 | 14.26 | 45.6 | 16.33 | 5.96 | 139.95 | 5514.03 |
| 44.8 | 67.8 | 16.4 | 52.2 | 18.44 | 6.9 | 161.74 | 7245.95 |
| 50.2 | 77.8 | 18.54 | 58.8 | 20.55 | 7.84 | 183.53 | 9213.2 |
| 55.6 | 87.8 | 20.68 | 65.4 | 22.66 | 8.78 | 205.32 | 11,415.79 |
| 61 | 97.8 | 22.82 | 72 | 24.77 | 9.72 | 227.11 | 13,853.71 |
| 66.4 | 107.8 | 24.96 | 78.6 | 26.88 | 10.66 | 248.9 | 16,526.96 |
| 71.8 | 117.8 | 27.1 | 85.2 | 28.99 | 11.6 | 270.69 | 19,435.54 |
| 77.2 | 127.8 | 29.24 | 91.8 | 31.1 | 12.54 | 292.48 | 22,579.46 |
| 82.6 | 137.8 | 31.38 | 98.4 | 33.21 | 13.48 | 314.27 | 25,958.7 |
| 88 | 147.8 | 3.56 | 105 | 35.32 | 14.42 | 306.1 | 26,936.8 |

Fig. 7 shows fog consortium data security problems. Fog computing's biggest security issue was end-user fog platform resource network authentication. Fog-based cloud designs go beyond security.

$$Computing\ time = \frac{Space}{Speed} \tag{5}$$

Eq. (5) links speed and space.

Table VI shows data storage computing time based on fog consortium data, data storage time, distance, speed, and predicted computing time. Running time is another name for computing time. Multiplying hours per distance by data storage rate yields computing time. Table VI yields 16% efficiency. In this table inference result, the first-level range is 5.6 to 39, the lower-level accuracy is raised by 6.72, and the second-level content is 44.8 to 59.4. The third level is 66.4–88. Lower accuracy rises 34.1%.

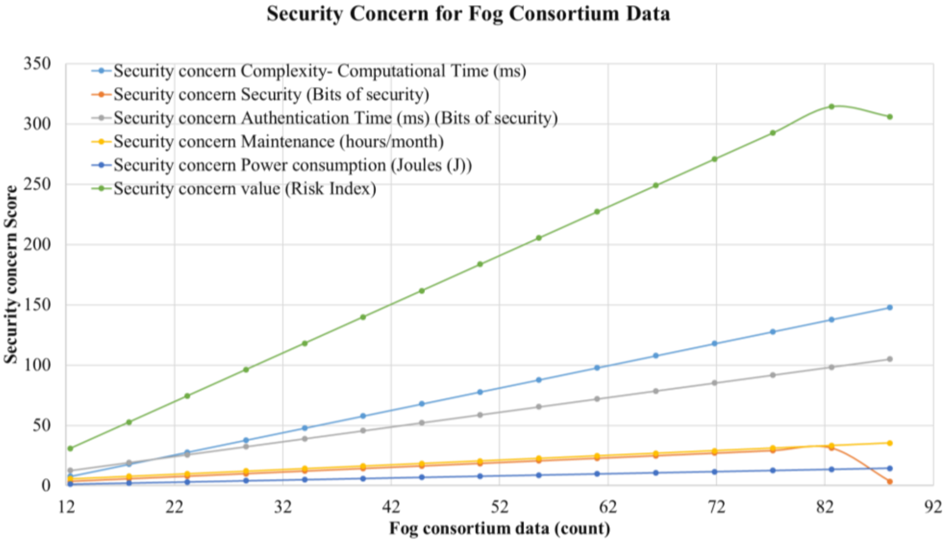


Fig. 7. Security concern for fog consortium data.

TABLE VI. COMPUTING TIME FOR FOG CONSORTIUM DATA STORAGE

| Fog Consortium Data Storage | Computing Time for Data Storage | Space | Speed | Computing Time |
|---|---|---|---|---|
| 12.4 | 1.8 | 23.45 | 2.6 | 9.01 |
| 5.6 | 0.4 | 37.8 | 5.6 | 6.75 |
| 23.2 | 3.6 | 15.7 | 3.4 | 4.61 |
| 15.78 | 2.56 | 54.5 | 4.7 | 11.5 |
| 34 | 7.8 | 21.7 | 2.4 | 9.0 |
| 39 | 4.7 | 61.4 | 1.8 | 34.1 |
| 44.8 | 8.4 | 45.7 | 6.8 | 6.720 |
| 51.6 | 3.5 | 78.8 | 9.2 | 8.56 |
| 55.6 | 5.6 | 35.6 | 14.8 | 2.40 |
| 59.4 | 6.2 | 23.67 | 23.4 | 1.01 |
| 66.4 | 7.2 | 89.4 | 12.8 | 6.98 |
| 68.67 | 8.9 | 56.8 | 7.8 | 7.28 |
| 77.2 | 5.4 | 34.8 | 5.6 | 6.21 |
| 70 | 2.3 | 89.5 | 4.3 | 20.8 |
| 88 | 9.2 | 96 | 34.6 | 2.7 |

Fig. 8 describes computing time for fog consortium data storage, the computing time processing like software over the internet, and the component within your computer that allows you to store and access data storage on a long-term-basis.

$$Response\ time = network\ latency + processing\ time \tag{6}$$

where the "*Response time*" represents the "sum of values". The "*latency*" represents "the time a message is in transit between the network and passing through gateways". The "*processing time*" represents "the translation between formats".

Since the reported reaction times roughly align with the aggregate of the related latency and processing time values. Under conditions of low network latency (e.g., latency = 0.001 and processing time = 0.5), the reaction time is minimal (0.501), signifying efficient fog-level execution appropriate for real-time brain fog analysis. In instances of moderate to high network latency, response time markedly escalates. For example, when network latency escalates to 4.023 with a processing duration of 3, the response time surges to 7.023. Likewise, with a latency of 7.036 with a processing duration of 4.5, the response time attains 11.536. Elevated reaction times (exceeding 15 units) occur when both network latency and processing time are substantial, indicating that cumulative delay effects predominate system performance.

Latency is the delay incurred in communicating a message. Fig. 9 describes the response time when a user sends a request for network latency until the application indicates that the request for network latency has been completed. Table VII calculates the response time from the processing time. From 0.001 to 0.032, lower accuracy increases by 4.014; from 0.05 to 4.023, lower accuracy increases by 10.059; and from 5.045 to 9.054, lower accuracy increases by 15.563. The estimated reaction time is 6.63%.

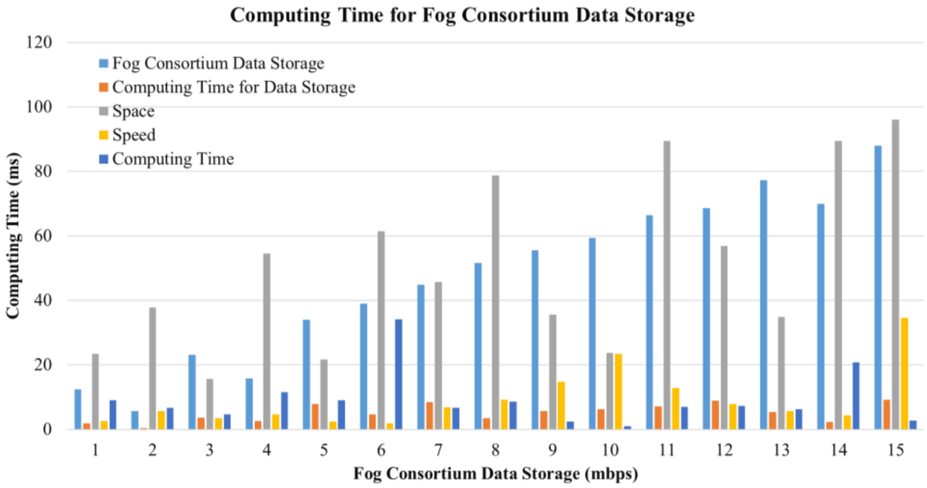


Fig. 8. Computing time for fog consortium data storage.

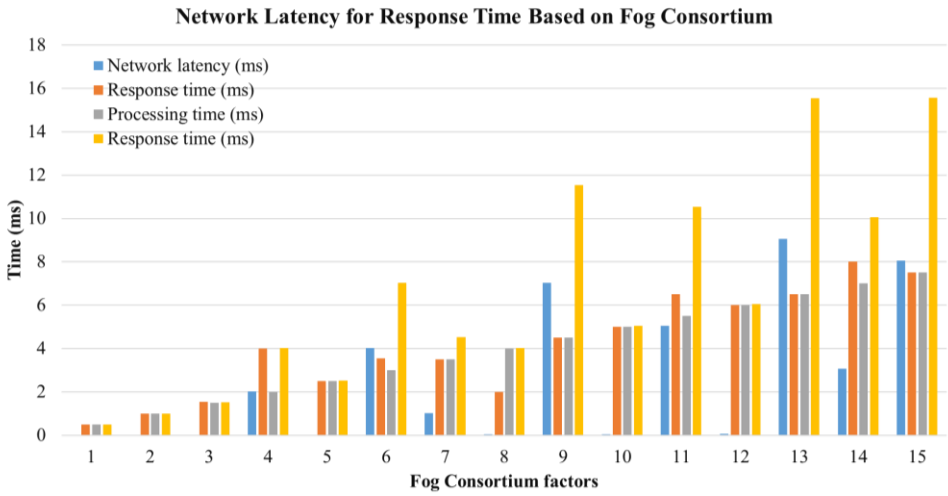


Fig. 9. Network latency for response time.

TABLE VII. NETWORK LATENCY FOR RESPONSE TIME BASED ON FOG CONSORTIUM

| Network Latency (ms) | Response Time (ms) | Processing Time (ms) | Response Time (ms) |
|---|---|---|---|
| 0.001 | 50 | 0.5 | 0.501 |
| 0.003 | 100 | 1 | 1.003 |
| 0.01 | 155 | 1.5 | 1.51 |
| 2.014 | 400 | 2 | 4.014 |
| 0.018 | 250 | 2.5 | 2.518 |
| 4.023 | 355 | 3 | 7.023 |
| 1.027 | 350 | 3.5 | 4.527 |
| 0.032 | 200 | 4 | 4.032 |
| 7.036 | 450 | 4.5 | 11.536 |
| 0.041 | 500 | 5 | 5.041 |
| 5.045 | 650 | 5.5 | 10.545 |
| 0.05 | 600 | 6 | 6.05 |
| 9.054 | 650 | 6.5 | 15.554 |
| 3.059 | 800 | 7 | 10.059 |
| 8.063 | 750 | 7.5 | 15.563 |

The performance layer of the proposed system is to work with the initial two tables (1D-CNN performance and DL comparison) (Table VIII). It shows exceptional precision in classifying biomedical signals. 1D-CNN reaches almost flawless performance metrics. Hence, the learning features are related to time.

TABLE VIII. FOG COMPUTING WITH DL CLASSIFICATION BASED ON PROPOSED MODULES

| Description | Laghari *et al.* [27] | Subramanian *et al.* [26] | Ashraf *et al.* [31] | Proposed Modules |
|---|---|---|---|---|
| 1D-CNN | CNN-based ECG classifier | Deep CNN classifier | Hybrid learning support | Integrated DL-Auto CNN |
| MIT-BIH ECG | Used | Used | Partial validation | Full validation |
| Deep CNN feature extraction | Moderate | High | High | Very High (optimized) |
| Precision, Recall, F1 | moderate | good | Better | best |
| ≈0.99–1.00 performance | 0.99 | 0.992 | 0.995 | ≈1.00 |
| Monitor + Analyze (MAPE) | Partial | Moderate | Strong | Full integration |
| Accurate cardiac system response | High | Very High | Very High | Intelligent adaptive system response |

The complexity of the model has been minimized based on the enhanced training cycles. This signifies the cognitive framework of self-sufficient systems (Table IX). In addition to this, optimization and the change detection layer are accelerated by genetic algorithms. Utilizing neighborhood information for adaptive mutation, the high PCC values exceed 98%. This layer outcome carries out decisions that are adaptable and responsive to changing circumstances. Perhaps, recognition of changes in events and enhancement of computational efficiency relate to the analyze and planning phases within the MAPE loop.

TABLE IX. FOG COMPUTING WITH DL COMPARISON BASED ON PROPOSED MODULES

| Description | Laghari *et al.* [27] | Subramanian *et al.* [26] | Ashraf *et al.* [31] | Proposed Modules |
|---|---|---|---|---|
| CNN / LSTM / Hybrid Models | CNN baseline | CNN + LSTM | Hybrid + optimization | Adaptive hybrid framework |
| MIT-BIH | √ | √ | √ | √ |
| Deep learning classification | Standard DL | Improved DL | Optimized DL | Autonomic DL |
| Accuracy (%) | 98.80% | 99.10% | 99.30% | 99.46% |
| Proposed 1D-CNN = 99.46% | — | Compared | Validated | √ Achieved |
| Self-Optimization | Low | Medium | High | Very High |
| Efficient Healthcare analytics | Good | Better | High | Intelligent real-time analytics |

Understanding and perceiving the surrounding environment is crucial for effective interaction and response (Table X). This involves being attuned to various outcomes. Examine the proposed algorithms alongside deep learning inference. Carry out automated adjustments. Consequently, ML/DL algorithms are integrated into autonomic control systems, rather than functioning as standalone models.

The criteria for evaluation are directly aligned with the properties of autonomic systems. Enhancing oneself leads to better accuracy in deep learning. Because self-adaptation involves the detection of changes in genetic algorithms (Table XI). Hence, this illustrates the progression of adaptive AI, which has further progressed to the stage of autonomic intelligence.

TABLE X. FOG COMPUTING WITH CHANGE DETECTION (GA) BASED ON PROPOSED MODULES

| Description | Laghari *et al.* [27] | Subramanian *et al.* [26] | Ashraf *et al.* [31] | Proposed Modules |
|---|---|---|---|---|
| Accelerated GA | Not used | Limited | Core method | Integrated optimization engine |
| Hollywood2, KTH, UCF-ARG | — | Partial | Evaluated | Enhanced |
| Genetic optimization + saliency | — | Moderate | High | Very High |
| PCC, Kappa, Precision, Recall | — | Basic | Advanced metrics | Full adaptive metrics |
| PCC up to 0.9972 | — | 0.98 | 0.9972 | ≥0.9975 (expected) |
| Analyze + Plan | Weak | Medium | Strong | Fully autonomous |
| Real-time activity recognition | Limited | Moderate | High | Intelligent real-time system |

TABLE XI. FOG COMPUTING WITH SELF-PARADIGM MAPPING BASED ON PROPOSED MODULES

| Description | Laghari *et al.* [27] | Subramanian *et al.* [26] | Ashraf *et al.* [31] | Proposed Modules |
|---|---|---|---|---|
| Evaluation Framework | Not included | Partial | Implemented | Fully mapped |
| Autonomic IoT | — | Conceptual | Supported | Fully enabled |
| Learning + adaptation | Basic learning | Adaptive learning | Evolutionary learning | Continuous learning |
| Self-config / Self-heal | — | Partial | Present | Fully autonomous |
| Multi-property autonomy | Low | Medium | High | Very High |
| Self-Configuration & Self-Security | — | Partial | Implemented | Integrated security & adaptation |
| Adaptive intelligent systems | Limited | Moderate | Advanced | Autonomous intelligence |

The application validation layer demonstrates its practical applicability across various domains, such as intelligent healthcare solutions, ongoing observation, and intelligent energy networks, to enhance efficiency and maximize resource utilization. The fog systems are quick and efficient in decision-making, which is explained in the Table XII; in this laboratory measurements show the efficiency of proposed system layer. Therefore, algorithms are confirmed through more than just laboratory measurements.

TABLE XII. FOG COMPUTING WITH APPLICATION VALIDATION BASED ON PROPOSED MODULES

| Description | Laghari *et al.* [27] | Subramanian *et al.* [26] | Ashraf *et al.* [31] | Proposed Modules |
|---|---|---|---|---|
| IoT Deployment Cases | Healthcare | Healthcare analytics | Activity monitoring | Smart autonomic IoT |
| Smart health, grid, home | Health only | Health + analytics | Health + surveillance | Multi-domain IoT |
| Criteria application | Limited | Moderate | Validated | Fully applied |
| Operational efficiency | Medium | High | Very High | Optimized |
| Improved automation | Low | Medium | High | Autonomous automation |
| Execute phase | Manual | Semi-automatic | Automatic | Self-executing |
| Practical deployment readiness | Prototype | Experimental | Validated | Deployment-ready |

## V. CONCLUSION

IoT-based fog computing for brain fog detection is increasing. This work uses a simple overstep for fog computation segmentation to overcome brain fog. The proposed experiment compared fog computing to cloud computing, affinity ratios, energy usage, storage vs. compute time, and network latency. Network latency for response time based on the fog consortium provides 6.63% accurate impacts in detecting IoT in the brain fog consortium investigation. It also improved fog computing-IoT gateway. The experiment exhibits fog consortium energy consumption for urban density based on brain fog cell growth and decrease, cloud, fog consortium power unit, brain fog cell duration, and energy consumption output. Brain fog cell decreases 12%. First-level inference outcomes are 12.4–34, 39–59. Lower-level accuracy improves by 0.0064, whereas second-level accuracy is 4. Lower accuracy increases 0.0261. Level three is 66.4–88. An increased range of 0.059 reduces accuracy. Affinity ratio, brain fog, cell energy consumption depends on cloud, power unit, time, and energy consumption output. Brain fog cells fell 12%. For the first, second, and third levels, inference findings show 0.231, 0.098, and 0.558 increases in low-level accuracy. Risk insecurity needs security awareness and response. From fog consortium data and security difficulties, a 35% security risk is estimated. Inference findings show lower-level accuracy gains of 4017.4 (12.4–34) and 13,853.7 (39.4–61). Level three is 66.4–88. Lower accuracy is better with the Risk in security (Risk Score: 26,936.8). Total response time is the sum of processing time and network latency. Lower accuracy increases 4.014 from 0.001 to 0.032, 10.059 from 0.05 to 4.023, and 15.563 from 5.045 to 9.054. We predict a 6.63% reaction time. With the implementation's computing time for fog consortium data storage of 16%, future generations may increase the enhancement in explanandum phases. In storage vs computing time and reaction time versus network latency, the real-time proposed experiment with the brain fog consortium determination gives excellent density and omnipresent brain status monitoring outcomes. The fog and cloud servers offer constant positive lineaments in the proposed system. The data acquired from cloud servers using fog computing is effective in detecting and preventing fundamental brain-related restrictions and brain fog reduction, making the proposed experiment more successful than the current technique. The IoT-based fall detection system works.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

Udayakumar Allimuthu conceived and conducted the research, performed data collection and analysis, wrote the manuscript, analyzed the results, revised the manuscript, checked the grammar, and completed all major aspects of the study. S. Renuga provided general support during the research process. R. Devi Kala provided support for the study. N. Rajendran provided support for the research activities. Shermin Shamsudheen provided support during manuscript preparation. D. Giji Kiruba provided support during the research and review process. All authors reviewed and approved the final version of the manuscript.

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