YOGIC: A Novel Deep Learning Approach to Quantify the **YOG**A-**I**nduced **C**ognitive Changes

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***Abstract*—This research investigates the impact of yoga on brain activity and cognition, employing Electroencephalography (EEG) cap technology. Yoga, a traditional practice renowned for its holistic benefits, has yet to be fully explored regarding its underlying neural mechanisms. Participants with prior yoga experience will undergo a structured yoga program, with pre- and post-intervention EEG recordings capturing brain activity changes. Utilizing the EEG cap, we will non-invasively record brain electrical activity during cognitive tasks and yoga practices, analyzing EEG signals for variations in brainwave patterns (alpha, beta, theta, delta) linked to cognitive functions like attention, memory, and emotion regulation. This study seeks to unveil potential changes in brain connectivity, cortical activation, and neuroplasticity induced by regular yoga practice. Moreover, psychological assessments will measure improvements in stress levels, mood, and overall quality of life. The findings hold the potential to illuminate the neural basis for yoga's cognitive benefits, offering insights for therapeutic applications in neurological and mental health conditions.**

***Index Terms*—Yoga, Brain-Computer Interface, Cognitive Science, Deep Learning, Electroencephalography, Genetic Algorithm, GA-LSTM, Long-Short Term Memory, Machine Learning, Non-invasive.**

I. Introduction

Yoga, deeply rooted in ancient Indian traditions, intertwines physical postures (asanas), controlled breathing (pranayama), and meditation techniques to create a versatile practice with profound mental health benefits. Originating thousands of years ago, yoga has adapted and integrated into diverse cultures, underscoring the enduring wisdom of these ancient practices that positively influence mental well-being.

The evolution of technology and the increasing affordability and accessibility of EEG devices have transformed our ability to non-invasively detect emotional states. This capacity finds valuable applications across diverse fields, from human-robot interaction to mental healthcare. It introduces an additional layer of interaction between users and technology, enabling the acquisition of tangible information without solely relying on verbal communication. This burgeoning field has led to a growing demand for autonomous classification methods that can interpret EEG data independently, reducing the need for expert analysis.

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One of the central objectives of our research project is to delve into the effects of yoga on cognitive function and brain activity. This investigation leverages EEG, an invaluable neurophysiological tool that captures electrical brain activity via electrodes placed on the scalp. EEG records the dynamic ebb and flow of electrical impulses within neurons, presenting insights into the ever-changing landscape of brain activity. It produces a continuous waveform represented across different frequency bands, each associated with distinct brain states.

Our research will involve recruiting participants from the community. The group will engage in a series of yoga practices. They will be subjected to a battery of cognitive function tests designed to evaluate aspects such as attention, memory, and executive function. During EEG recording sessions, participants will be guided to relax with their eyes closed, facilitating the measurement of baseline brain activity during a state of repose. Moreover, EEG data will be collected while participants engage in cognitive tasks, enabling us to understand how yoga influences brain function across various mental activities.

Within the fields of neuroscience and cognition, human brain activity is characterized by a spectrum of brain waves. These can be categorized into five primary types based on their frequencies: Delta, Theta, Alpha, Beta, and Gamma. Delta waves are slow and associated with deep sleep, while Theta waves are related to creativity and relaxation. Alpha waves signify a relaxed, alert state, Beta waves are associated with active thought, and Gamma waves indicate heightened consciousness. This study explores these brain waves, aiming to understand their distinctive attributes and potential implications for cognition and well-being.

Our research hypotheses propose that participants in the yoga group will demonstrate significant improvements in cognitive function, notably enhanced attention, memory, and executive function. These improvements are expected to be complemented by specific changes in EEG activity. During moments of rest, we anticipate an augmentation in alpha and theta power within the group, which reflects a deeper state of relaxation and meditative awareness. During cognitive tasks, we expect to observe improved event-related potentials, and neural responses closely tied to specific cognitive processes.

By delving into the neural mechanisms underpinning the effects of yoga on cognitive function, this research endeavour aims to enrich our understanding of the holistic benefits of yoga and its potential applications in enhancing mental well-being. Our findings may offer valuable insights into how yoga practices influence brain activity, paving the way for the development of targeted interventions aimed at stress reduction, mood enhancement, and cognitive improvement.

For instance, if specific brain regions consistently reveal an influence from yoga, our research may inform the design of yoga-based interventions that directly target these areas to address particular mental health conditions or cognitive challenges. Understanding these effects could potentially usher in novel pathways for integrating yoga practices into mental health and wellness programs, where they could play a pivotal role in supporting holistic well-being.

Furthermore, our research envisions a realm where the integration of yoga practices into mental health and wellness programs is significantly enhanced by a deeper understanding of the neural mechanisms involved. These interventions could be tailored to cater to specific populations, including individuals struggling with anxiety disorders, depression, or cognitive impairments. In such a scenario, yoga might evolve into an adjunct or complementary therapy within mental health treatment plans, thereby promoting comprehensive well-being and, potentially, reducing the dependence on pharmacological interventions.

The scientific exploration of the neural effects of yoga also offers a fertile ground for interdisciplinary collaboration. It brings together experts from the realms of neuroscience, psychology, and yoga research, fostering a rich exchange of knowledge and insights. This cross-disciplinary approach enriches our understanding of the intricate connections between the mind, body, and brain. It offers a more comprehensive perspective on the mechanisms through which yoga influences mental health and well-being.

In summation, our research venture, by investigating the neural mechanisms underlying the effects of yoga on cognitive function, seeks to contribute not only to the scientific literature but also to the broader discourse on mental health and well-being. The knowledge gleaned from these studies may pave the way for the development of evidence-based yoga interventions, propelling yoga into a more widely recognized and effective tool for promoting mental well-being and supporting mental health initiatives across diverse and dynamic populations. This research holds the promise of transforming our approach to mental health and well-being, bringing the age-old wisdom of yoga into the contemporary landscape of mental healthcare.

A. Related Works

Various non-invasive methods to obtain data could potentially correlate with conscious arm movement. Past work in the subject has used everything ranging from EEG to EMG and even EOG as input to perform these predictions. Out of all of these EEG is broadly accepted to be the most practical dynamic measure of brain activity [1], [2], [3], [4], [5], [6]. Deep learning, machine learning and statistical methods have been used to obtain the predicted movement from these data sources.

Most prior research related to limb motion intention classification such as Hong *et al.* [7], Diwakar *et al.* [8], Idowu *et al.* [9] and Miskon *et al.* [10] utilize EEG as the input data for the classifier. Miskon *et al.* [10] and Abdel-Samei *et al.* [11] both proposed the use of EOG (Electrooculography) signals to predict intended limb movement. Abdel-Samei *et al.* [11] found the system to be accurate and reliable. Bandara *et al.* [12] presented the advantages of using EEG over EMG as the data source for multi-degree-of-freedom movements. Parr *et al.* [13] proposed a novel gaze training approach utilized along with EEG alpha waves. This method allows pre-emptive outputs from the predictor. It was found to pose less cognitive burden and showed better results when compared to an EEG alone. Li *et al.* [14] used sEMG along with EEG for upper limb motion classification. They found a significant improvement in classification accuracy when using the dual-signal combined data (sEMG-EEG) compared to single-signal data (EEG).

Signals obtained using non-invasive techniques such as EEG and EMG tend to be very noisy and make any accurate classification difficult. To mitigate the loss in information due to noise the signals need to be cleaned before being passed to the classifier. Various different approaches for data cleaning and denoising have been utilized in existing works. Hong *et al.* [7] used multiple filters such as a band pass filter and DWT filter to clean the signals obtained from an EEG headset. Sundararajan *et al.* [15] proposed using a domain variant of the stationary subspace analysis technique (DSSA) to reduce noise in EEG data and found this method increased the accuracy of a model designed to classify food choices using brain waves by 10%. Miskon *et al.* [10] proposed using fast Fourier transforms and independent component analysis for data pre-processing.

Once the data has been cleaned and pre-processed, it is passed to the classifier to obtain the limb movement intention classification result. Various methods can be used to create this classifier, including machine learning and deep learning models. Li *et al.* [14] used a linear discriminant analysis (LDA) classifier on combined sEMG and EEG signals to obtain upper limb motion intention. Hong *et al.* [7] used filtered EEG data on a support vector machine (SVM) to obtain compound motion classifications such as 'Up Down vs Left Right'. Bousseta *et al.* [16] used 14 channel EEG signals on an SVM to obtain the classification of four-movement classes and found the model to give highly accurate results. Roy *et al.* [17] compared various machine learning models such as decision trees, quadratic discriminant analysis and SVM on the shoulder and elbow joint movement classification and found the SVM to have the best results. Bandara *et al.* [12] offered a comparison between KNN and a neural network for classification and found the neural network performs far better.

Srinivasa Prabhu K. [18] compared deep learning and machine learning approaches ranging from Decision Trees and Random Forests to CNNs on Binary classification for hand movement using EEG signals. They found CNN to have the best performance by a wide margin. Lu *et al.* [19] used a classifier based on restricted Boltzmann machines to obtain motor imagery classifications. This approach combined feature extraction and classification into a single pipeline. As a result, they found train times to be significantly higher, but the model proved far more efficient in real-time prediction applications. Idowu *et al*. [9] proposed a novel stacked sparse auto-encoder (SSAE) model that achieved very high accuracy in EEG-based motion classification and far better performance in multiple Degree-of-Freedom motions than other models such as ANN, SVM and LDA. This paper also concluded that better performance was achieved when a non-linear activation function was used for the encoder layer and a linear activation function was used for the decoder layer of the auto-encoder. Wang *et al*. [20] proposed an LSTM model to utilize the time-dependent features of EEG. Zhang *et al*. [21] proposed an approach to the merged data augmentations with a deep learning model using empirical mode decomposition. They used this and a convolutional and wavelet neural network to train weights.

There are various EEG, EMG and multimodal datasets that can be used to train a model on limb movement intention tasks. Jeong *et al*. [22] presented a large 60-channel EEG, 7-channel EMG and 4-channel EOG dataset collected on 25 subjects over three days for a total of 82,500 trials. [23] is the data obtained in the trials conducted. Ofner *et al*. [24] analyzed the encoding of single upper limb movements in the time domain of low-frequency electroencephalography (EEG) signals and presented a 61-channel EEG dataset for upper limb movement. This data was captured from 15 healthy subjects for six classes of upper limb movement. This was the dataset utilized in this paper to evaluate the proposed scheme.

B. Motivation

In this paper, we have designed a model named YOGIC, a pioneering deep-learning endeavour, that aims to unravel yoga's impact on cognition via EEG cap technology. This innovative approach delves into the complex interplay between yoga practices and cognitive shifts, offering insights for tailored well-being strategies and potential advancements in cognitive rehabilitation and assistive technologies. It mainly targets the following five potential applications:

- **Unraveling Yoga's Cognitive Impact:** YOGIC aims to decipher how yoga influences cognition using advanced deep learning and EEG cap technology.
- **Detailed Neurological Understanding:** This approach seeks to offer detailed neurological insights into the specific cognitive changes induced by different yoga practices.
- **Integration of Science and Yoga:** Bridging cognitive science and yoga, YOGIC provides a scientific lens to quantify and understand yoga's cognitive benefits.
- **Tailored Well-Being Insights:** YOGIC's outcomes may enable personalized well-being strategies by elucidating how diverse yoga practices affect individual cognitive states.
- **Innovative Therapeutic Potential:** YOGIC's findings hold promise in inspiring novel therapeutic approaches, potentially reshaping cognitive rehabilitation and assistive technologies.

C. Contribution

The primary contribution of this paper is to present a model that contributes by accurately categorizing mental states (relaxed, stressful, neutral). It scientifically quantifies yoga's impact on these states, validating how yoga distinctly influences mental well-being.

- **Accurate Classification:** The model accurately classifies relaxed, stressful, and neutral mental states, facilitating precise identification and differentiation between these states. We have proposed a novel deep learning model, based on LSTM, to find the most optimal set of hyperparameters to get the best prediction accuracy. These hyperparameters include window size, number of units in an LSTM layer and number of epochs for training.
- **Scientific Validation of Yoga's Impact:** It quantifies the scientific impact of yoga on mental states, providing empirical evidence on how yoga practices distinctly influence and benefit our state of mind.

D. Organisation

The rest of the paper is organised as follows. In section II, the proposed methodology has been discussed. In Section III, we understand the system description using mathematical modelling and flowcharts. The results and discussions are presented in Section IV. The paper is finally concluded in Section V.

II. METHODOLOGY

The research methodology unfolded in two interconnected phases, each designed to provide a comprehensive understanding of the impact of yoga on cognitive function. In the initial phase, the "mental_state.csv" dataset, curated from Bird et al.'s (2018) study, underwent meticulous examination to ensure a balanced representation of mental states. A preprocessing pipeline, including normalization and a strategic 70-30 split for training and testing sets, was implemented within the framework of an experimental design.

Model development encompassed the exploration of diverse architectures, with the eventual selection of an LSTM model known for its adeptness in capturing temporal dependencies within EEG data. The hyperparameters of the LSTM model underwent meticulous optimization using the Keras Tuner library, followed by training with early stopping mechanisms to prevent overfitting. Evaluation on a distinct test set provided a comprehensive assessment through metrics such as accuracy, loss, and visual representations like confusion matrices and classification reports.

In the second phase, participants were systematically recruited for a more personalized investigation. Pre- and post-yoga intervention data were collected, offering a unique opportunity to observe real-world impacts. This newly acquired data was then fed into the pre-trained LSTM model, enabling the extraction of insights into the intricate relationships between yoga, neural responses, and psychological well-being.

Throughout both phases, ethical considerations remained paramount, with a steadfast commitment to informed consent and participant confidentiality. Rigorous statistical analyses were a consistent thread, allowing for meaningful interpretations while acknowledging inherent limitations such as sample size constraints.

This dual-phase, integrated methodology contributes not only to the nuanced understanding of the connections between yoga and cognitive function but also enriches the broader comprehension of the intricate interplay between mind-body practices and mental states. As a roadmap for future endeavours, the envisioned expansion of the dataset and exploration of advanced deep learning architectures aim to further enhance predictive performance.

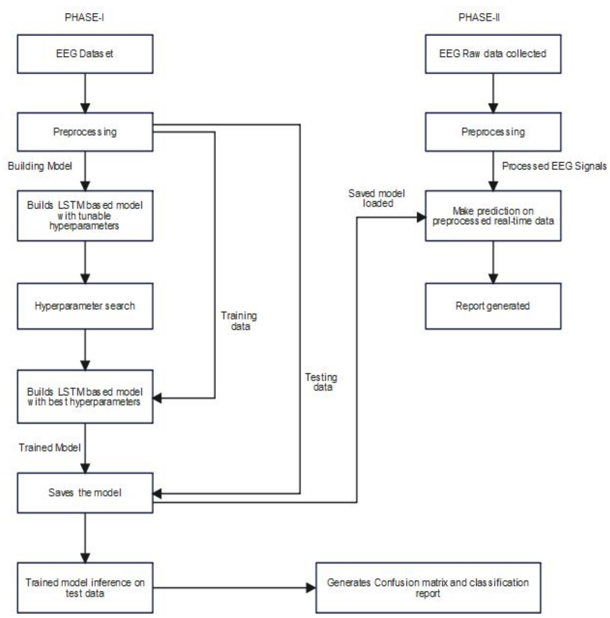

Figure 1: GA-LSTM model workflow.

A. Data Set Description

The data was collected from four people (2 males, and 2 females) for 60 seconds per state - relaxed, concentrating, neutral. A Muse EEG headband was used which recorded the TP9, AF7, AF8 and TP10 EEG placements via dry electrodes.

B. Data Pre-processing

The dataset preprocessing for this EEG-based mental state classification project involved several key steps. The dataset, obtained from the study by Bird et al. (2018), was loaded and systematically examined to understand its structure. A segment of the EEG data, specifically ranging from 'freq_010_1' to 'freq_750_1', was visualized to gain insights into its distribution. The distribution of labels representing different mental states was assessed to ensure a balanced representation. The dataset was split into features and labels, and a preprocessing function was employed for a 70-30 train-test split.

C. Model Creation

The model creation process involved constructing a Long Short-Term Memory (LSTM) neural network for EEG-based mental state classification. Initial hyperparameter tuning was conducted using the Keras Tuner library, optimizing parameters like dropout rate, hidden dimensions, and the number of LSTM layers through a random search. The resulting architecture consisted of stacked LSTM layers, transforming input data through flattening to facilitate classification into three mental states using softmax activation. Compilation utilized the Adam optimizer and sparse categorical cross-entropy loss function, with accuracy chosen as the evaluation metric. The training was executed on preprocessed data with early stopping to prevent overfitting. The model underwent hyperparameter optimization, seeking the most effective configuration. Evaluation on a reserved test set provided metrics such as accuracy and loss, while visualizations of training history, confusion matrices, and classification reports offered a comprehensive understanding of the model's performance, establishing a robust framework for EEG-based mental state classification.

Long Short-Term Memory (LSTM)- Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture that is particularly effective in capturing and learning long-term dependencies in sequential data, making it suitable for time series and sequential tasks such as EEG data analysis. How LSTM Works:

1. Memory Cells:

- LSTMs have memory cells that can store information over long periods, mitigating the vanishing gradient problem that standard RNNs face.

2. Gates:

- LSTMs use three gates:
- Forget Gate: Determines what information from the cell state should be thrown away or kept.
- Input Gate: Updates the cell state with new information.
- Output Gate: Produces the output based on the cell state but in a filtered manner.

3. Cell State:

- The cell state runs straight down the entire chain, with only minor linear interactions. This allows information to flow unchanged if the forget gate keeps it, and to be updated otherwise.

4. Hidden State:

- The hidden state, or output, is a filtered version of the cell state. It carries information about the parts of the memory that the model has decided to pass on.

The LSTM cell involves several mathematical operations, denoted as

- h_t as the hidden state at time t,
- c_t as the cell state at time t,
- x_t as the input at time t,
- f_t as the forget gate at time t,
- i_t as the input gate at time t,
- o_t as the output gate at time t,
- W and U as weight matrices, and
- b as bias.

The LSTM cell involves the following computations:

- **Forget Gate:**

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

- **Input Gate:**

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

- **Update Cell State:**

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t$$

- **Output Gate:**

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(c_t)$$

These equations define how an LSTM cell processes input, updates its memory and produces output. This ability to selectively learn and forget information over long sequences is crucial for capturing dependencies in time-series data like EEG signals. In your project, the LSTM is trained to understand and predict patterns in EEG data associated with different cognitive states influenced by yoga practices.

III. System description and mathematical background

This section describes the work of our proposed model mathematically and illustratively.

A. *Long Short–Term Memory (LSTM)*

LSTM is the most fundamental building block of our proposed model. The LSTM block was specifically designed to remember both long-term and short-term dependencies and to fix the problem of vanishing gradients in vanilla RNN. Fig. 2 shows the LSTM cell structure. Inputs to an LSTM cell include x_t (current input), h_{t-1} (previous hidden state) and C_{t-1} (previous memory state) and output from the LSTM cell are h_t (current hidden state) and C_t (current memory state). This structure contains a memory cell and three gates. The functions of all the gates and cell memory are defined below. The Sigmoid and Tanh functions used in LSTM cells are shown in equations (1) and (2).

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{1}$$

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

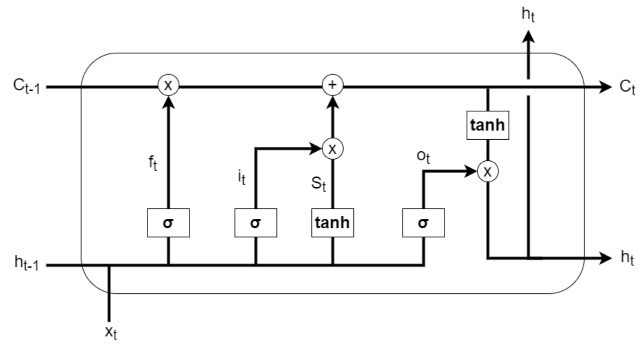

Figure 2: LSTM cell structure diagram.

- *Input Gate:* The purpose of the input gate is to add filtered knowledge from the current input to the previously learned information. Equations (3)-(4) shows input gate and candidate layer output where x_t, h_{t-1} are current input and previous hidden state while W and U are the weights.

$$i_t = \sigma(x_t U^i + h_{t-1} W^i) \tag{3}$$

$$S_t = \tanh(x_t U^g + h_{t-1} W^g) \tag{4}$$

- *Output Gate:* The purpose of this gate is to calculate the output o_t and hidden output h_t. These are computed using equations (5)-(6).

$$o_t = \sigma(x_t U^o + h_{t-1} W^o) \tag{5}$$

$$h_t = \tanh(C_t) * o_t \tag{6}$$

- *Forget Gate:* This gate determines which information from the previous states is to be discarded from the cell memory. This is computed using equation (7).

$$f_t = \sigma(x_t U^f + h_{t-1} W^f) \tag{7}$$

- *Cell Memory:* The cell memory contains all the important information from the previous states so that it is not lost due to vanishing gradients. The cell memory is updated by every LSTM cell using equation (8) where $C_t, C_{t-1}, f_t, i_t, S_t$ represents current memory state, previous memory state, forget gate output, input gate output and candidate layer output.

$$C_t = \sigma(f_t * C_{t-1} + i_t * S_t) \tag{8}$$

B. *Genetic Algorithm (GA)*

GA is the technique used to tune the parameters of a model. This technique is a search heuristic that is inspired by the natural evolution theory. The fittest individuals are chosen to be part of the reproduction process wherein offspring are produced for the next generation. Each generation will have a specified population: the number of chromosomes in every iteration. We start with an initial population where one individual in a population is one chromosome or one solution to our problem. Every chromosome is tested by obtaining its fitness value using a fitness function. The fittest chromosomes are taken as parents for the next generation. The selection of these parents is made using a selection method where the fittest parents have a higher chance of selection, but the less fit parents also have a slight chance of being selected. New offspring of the parents are generated using mutation or crossover techniques. The successive generations produce fitter populations than their predecessors. The algorithm converges when the subsequent generations are not significantly better than the previous generations. A primary pipeline of the genetic algorithm can be seen in Fig. 3.

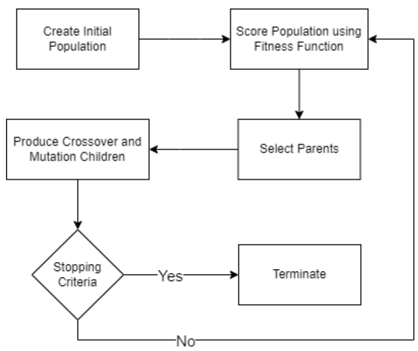

Figure 3: Basic genetic algorithm pipeline.

- *Chromosome:* In every generation, there is a population. In every population, there are multiple individuals. Individuals are characterised by certain parameters called genes which join into strings to form Chromosomes(solution). These strings are usually binary for ease of calculation.
- *Fitness function:* The fitness function represents an individual's fitness, i.e. its ability to face off with other individuals. The probability of each individual being selected for reproduction depends on its fitness score. This fitness function is highly dependent on the problem statement, and for example, if we are trying to minimise the sum of all genes, then the fitness function can be the negative sum of all genes in the chromosome.
- *Selection:* In the selection phase, we select the parents whose genes will be passed to the next generation. The fittest parents have a higher chance of getting selected than those who are not fit (determined by a fitness function). Several selection methods exist, for example, roulette wheel selection, rank selection, tournament selection etc.
- *Crossover:* The utmost important phase in a genetic algorithm is Crossover. In this process, a crossover point is chosen randomly for each pair of parents to be mated, and the offspring are created by swapping the genes of both parents until they reach the crossover point. It is visualized in Fig. 4.
- *Mutation:* This method takes one parent and flips some randomly chosen bits in the string. It is done to maintain diversity within the population and prevent any convergence at an early stage. It is visualized in Fig. 4.

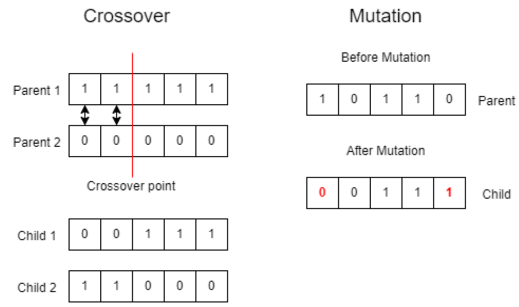

Figure 4: Crossover and Mutation visualization.

C. GA-LSTM

In this section, we will combine the previous two sections. Our approach uses an LSTM model whose parameters are tuned using GA. The hyperparameters to be tuned include the number of units in an LSTM layer, the input window size for our time-series data and the number of epochs for which our model will be trained on the dataset. The architecture of our proposed model can be seen in Fig. 5. We initially start from a randomised population and terminate the process when we reach the termination condition, triggered after a certain number of generations are finished or after the successive generations stop being significantly better than the previous generations.

The loss generated on the test dataset by the LSTM model is considered the fitness score. So, a lower fitness score is considered to be fitter by the GA algorithm. The LSTM model architecture consists of two LSTM layers followed by a Dense layer. The algorithm for training our approach can be seen in Algorithm 1. Window size creates the train, Val and test data in time-series format. Both window size and number of units will be used to define the model architecture, and finally, the number of epochs will be used for training the model. Roulette wheel selection is used for selecting parents for the next generation. Ordered crossover and shuffle mutation used to generate children.

IV. Results

A. Subject(s) Training

Our experiment involved training deep learning models using the EEG signals captured from the subjects and further classifying the movement based on the captured EEG signals. We took data from 15 healthy subjects for our experiment, adults aged 22-40 with an average age of 27 years. Six subjects were males, and the remaining were females. Apart from subject 1, all were right-handed.

The data was acquired from *"Upper limb movement decoding from EEG (001-2017)"* [24] dataset of BNCI Horizon 2020. The data consisted of 10 runs for each subject with an approximate total of 16 lakh entries per subject. The subjects performed six movement types: elbow up/down, wrist ProSupination, i.e. wrist rotation, and gripping movement, which included hand open/close, all with the right upper limb. All movements started at an evenhanded position with the

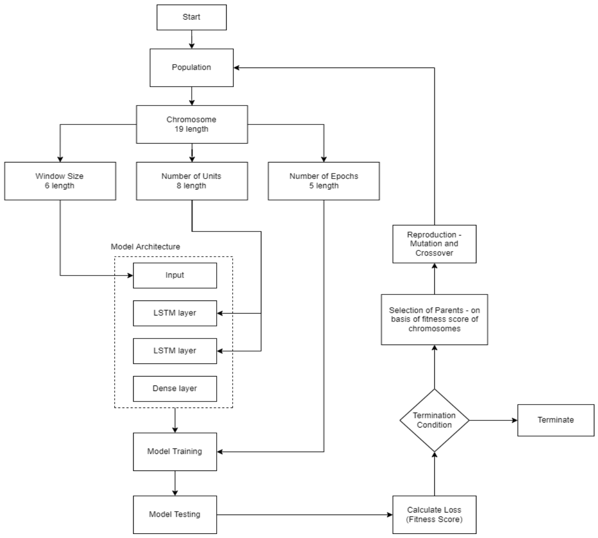

Figure 5: GA-LSTM model workflow.

following characteristics: They were to keep their hand half-open with the thumb on the inner side and the lower part of the arm extended by 120 degrees. In addition to the six mentioned movement classes, Subjects were asked to stay still in their mean position to capture data for the rest class. The data was collected in two sessions on two separate days with a difference of not more than a week. In the first session, subjects were instructed to execute movements, whereas, in the second session, they were asked to perform kinesthetic motor imagination. The data set comprised GDF files for each subject, session, and run. Fig. **??** shows the channel labels indicating various electrode positions, with the EEG electrodes at (1-61), the EOG electrodes at (62-64), the data glove sensors at (65-83), and the other sensors linked with exoskeleton at (84-96). For our experiment, we only used the data acquired during the first session, which involved motor execution by the subjects and the channels indicating the EEG electrode positions (1-61).

- *Long Short-Term Memory (LSTM)*: Initially, we used the LSTM model to classify movements from the captured EEG signals. The results obtained were surprisingly 90% better than those achieved from ANN. The corresponding losses obtained after running our LSTM model on each of our 15 subjects with window size, number of epochs and number of units as 10, 10 and 50 are mentioned in Table
- *GA-LSTM*: The genetic Algorithm combined with the LSTM model provided us with more optimised results than we achieved from the LSTM Model. The genetic algorithm is applied to get each subject's best window, epoc and unit size based on its captured EEG signals. This led to a decreased loss for each subject and better classification accuracy. The best window size, number of epochs and units calculated for each subject is also mentioned in Table

Data: $initial\_population$
Data: subject data - train, val and test
Result: $best$
$population\_size \leftarrow 4$;
$num\_generations \leftarrow 4$;
$population \leftarrow initial\_population$;
$best \leftarrow population[0]$;
$best\_loss \leftarrow inf$;
$i \leftarrow 0$;
for $i \leq num\_generations$ **do**
    $j \leftarrow 0$;
    for $j \leq population\_size$ **do**
        $gene \leftarrow population[j]$;
        $window\_size \leftarrow gene[0:6]$;
        $num\_units \leftarrow gene[6:14]$;
        $epochs \leftarrow gene[14:]$;
        if $window\_size$ *is 0 or* $epochs$ *is 0 or* num_units *is 0* **then**
            $j++$;
            Continue;
        end
        $loss \leftarrow fitness(window\_size, num\_units, epochs)$;
        if $loss \leq best\_loss$ **then**
            $best\_loss \leftarrow loss$;
            $best \leftarrow gene$;
        end
        $j++$;
    end
    $i++$;
end

Algorithm 1: GA-LSTM Training

B. Discussion

This study successfully classified six different arm movements from time-domain EEG, captured at low frequencies. Significant classification accuracies were reached during the prediction of the executed movements of the upper limb of the right arm. It proved that the time-domain EEG signals could be decoded into body movements performed singly and non-repetitively and differentiated against each other.

We found that the Neural Networks adopt a different paradigm that combines feature extraction and classification into a single pipeline. Its training takes a long time, and once a model is trained, it can be directly applied to real-time, which is more efficient than other algorithms. Initially, using the LSTM Model for classification led to the provision of 90% better results than the classic ANN model. But we found that for different subjects, accuracy will vary for the fixed window, epoc and unit size of the LSTM model for all subjects. The learning and thinking capability of a person differs from one another. Therefore, tuning these parameters is required for better accuracies in classifying their generated EEG signals.

The genetic algorithm searches parallel from a population of points. Therefore, it is best to avoid the optimal local solution like various traditional methods, which search from a single point. Thus, applying the GA-LSTM Model provided us with the best parameters for each subject, which gave a more optimized classification with an average increase of 19.55% in totality.

To demonstrate our predicted results, we used PyBullet, in which we tried to simulate a virtual prosthetic based on our predictions. We performed elbow up/down, wrist ProSupination and hand open/close. Fig. **??** shows the simulator we used to demonstrate the movement predicted using our GA-LSTM model.

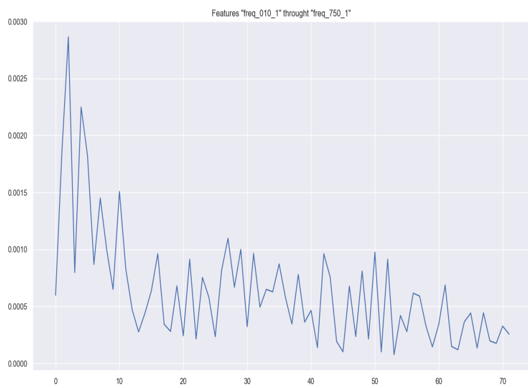

Figure 6: Features in dataset

Figure 7: Model Accuracy

V. Conclusion

We have demonstrated the successful classification of mental states based on the captured time-domain EEG signals, which are low-frequency, using the LSTM model with much higher classification accuracies. The accurate classification of mental states and the scientific validation of yoga's impact present promising applications. From personalized well-being interventions and stress management strategies to informing advancements in cognitive rehabilitation and assistive technologies, our findings pave the way for tailored approaches in mental health care. Moreover, the insights gained contribute to the scientific understanding of yoga's role in enhancing

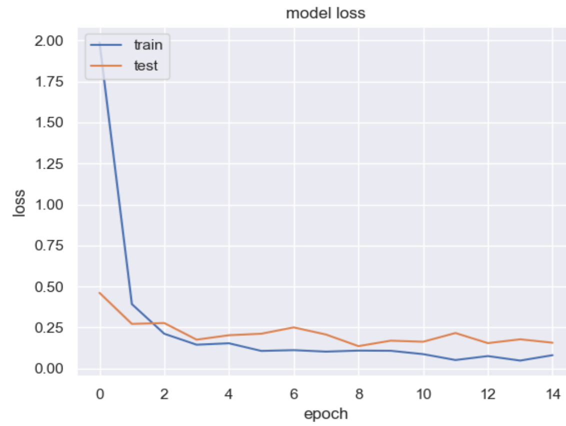

Figure 8: Model Loss

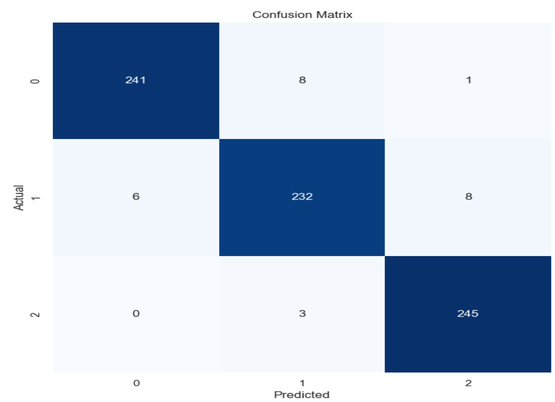

Figure 9: Confusion Matrix

Figure 10: EEG Cap

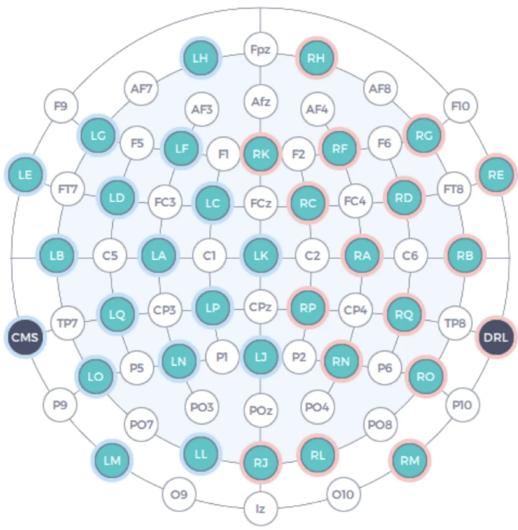

Figure 11: Channel Labels

mental well-being, opening avenues for further research and innovative interventions.

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