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Simulation of Leaky Integrate-and-Fire with Random Forest Regression

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Abstract: Neural network models play a crucial role in understanding the complex dynamics of neuronal spiking activities in the brain. Among these models, the Leaky Integrate-and-Fire (LIF) neuron model has been widely used due to its simplicity and efficiency. However, accurately simulating the spiking behavior of LIF neurons remains a challenging task. Current research efforts often face limitations in accurately capturing the nonlinear dynamics and spike timing precision of LIF neurons. To address this issue, this paper proposes a novel approach that combines the LIF neuron model with Random Forest Regression. This innovative methodology aims to improve the accuracy and efficiency of simulating neuronal spiking activities. The incorporation of Random Forest Regression enables better prediction of the spiking behavior of LIF neurons, providing a more precise model for studying neural network dynamics.

Keywords: *Neural Networks; Neuronal Spiking; Leaky Integrate-and-Fire; Random Forest Regression; Spike Timing Precision*

1. Introduction

Leaky Integrate-and-Fire (LIF) is a field of study in computational neuroscience focused on modeling the behavior of neurons in response to input signals. The LIF neuron model simplifies the complex biological processes of real neurons to capture essential features, making it suitable for large-scale neural network simulations. However, current research faces several challenges and bottlenecks. One major hurdle is finding efficient algorithms to accurately simulate the dynamics of LIF neurons in real-time while maintaining biological realism. Additionally, there is a need for better understanding the impact of parameter variations on network behavior and developing methods to optimize these parameters for specific applications. Addressing these issues will be crucial for advancing the field of LIF modeling and its applications in neuroscientific research and artificial intelligence.

To this end, research on Leaky Integrate-and-Fire models has advanced to include sophisticated computational simulations and experimental validations, exploring intricate dynamics of neural networks. Interdisciplinary collaborations have led to novel insights into information processing in the brain, pushing the boundaries of understanding neuronal behavior. A literature review on leaky integrate-and-fire (LIF) neuron models in spiking neural networks (SNNs) reveals a range of innovative approaches. Huang et al. [1] introduce the Complementary LIF (CLIF) neuron, addressing accuracy issues in training SNNs by enabling backpropagation in computing temporal gradients. Mohanan et al. [2] optimize LIF neuron circuits using nanoporous graphene memristors for enhanced area efficiency. M A et al. [3] present an energy-efficient LIF neuron model with a Schmitt trigger-based spike generator for distortion prevention. Takada et al. [4] explore noise-induced synchronization in LIF circuits with dead zones to enhance simultaneous firing rates. Zhu et al. [5] develop an LIF neuron based on organic electrochemical transistors for temporal-coding SNNs. Qin et al. [6] study threshold switching memristors for nociceptive and LIF neuron simulations. Shiu et al. [7] create a computational model of the Drosophila brain based on LIF neurons, demonstrating insights into sensorimotor processing. Kang et al. [8] propose a quick LIF mechanism for SNNs to reduce computation complexity while maintaining performance. Lastly, Deb et al. [9] design an adaptive LIF neuron model for neuromorphic circuit applications, achieving efficiency and compactness. Gao et al. [10] introduce a calcium-gated bipolar LIF neuron model and a quantization-aware training framework for high-accuracy ANN-to-SNN conversion. A literature review on leaky integrate-and-fire (LIF) neuron models in spiking neural networks (SNNs) showcases various innovative approaches. The utilization of Random Forest Regression in such analyses is crucial due to its capability to handle complex nonlinear relationships and high-dimensional data, making it well-suited for predicting outcomes in intricate neural network models like those discussed in the reviewed studies.

Specifically, Random Forest Regression and Leaky Integrate-and-Fire models are both utilized in scientific research for data analysis and prediction. While Random Forest Regression focuses on ensemble learning and decision trees, Leaky Integrate-and-Fire models are commonly employed in neural network simulations to study neuronal activity patterns. In recent literature, a novel approach combining adaptive thermal clothing, IoT, and Random Forest Regression (RFR) has been proposed for enhancing outdoor comfort [11]. Another study focused on estimating the state of charge in lithium-ion batteries using an optimized RFR algorithm for electric vehicles [12]. Additionally, the use of RFR and IoT data in predictive road sign maintenance has also been explored for improving maintenance accuracy and cost-effectiveness [13]. Furthermore, the comparison of linear regression, neural networks, and RFR in predicting air ozone levels using soft sensor models has been investigated [14]. Moreover, an optimized RFR model for Li-ion battery prognostics and health management has been developed, showing improved accuracy in SOH estimation and RUL prediction [15]. Furthermore, the application of RFR in predicting gold prices has been studied [16]. An analysis comparing linear regression, RFR, and Gradient Boosted Trees Regression for predicting house prices has been conducted, with RFR showing the highest accuracy

[17]. Lastly, a hybrid method utilizing RFR and the Whale Optimization Algorithm for pavement maintenance optimization has been proposed, demonstrating enhanced accuracy compared to traditional approaches [18].

However, current research still faces limitations in addressing scalability, real-time processing constraints, and potential overfitting issues when applying Random Forest Regression (RFR) in complex systems requiring high accuracy and robustness. To overcome those limitations, this paper aims to enhance the accuracy and efficiency of simulating neuronal spiking activities, specifically the spiking behavior of Leaky Integrate-and-Fire (LIF) neurons, which have posed challenges due to their nonlinear dynamics and spike timing precision. The proposed approach integrates the LIF neuron model with Random Forest Regression, a novel methodology designed to address these challenges. By combining the simplicity and efficiency of the LIF model with the predictive power of Random Forest Regression, this method offers a more precise model for studying neural network dynamics. The incorporation of Random Forest Regression into the simulation process enables improved prediction of LIF neuron spiking behavior, leading to a more comprehensive understanding of the complex dynamics of neuronal activities in the brain. This innovative technique represents a significant advancement in the field of neural network modeling, providing researchers with a valuable tool to overcome existing limitations and drive further exploration into the intricate mechanisms underlying neuronal spiking activities.

Section 2 of the study delves into the problem statement, focusing on the challenges associated with accurately simulating the spiking behavior of Leaky Integrate-and-Fire (LIF) neurons. Section 3 introduces the proposed method, a novel approach that combines the LIF neuron model with Random Forest Regression to enhance the accuracy and efficiency of simulating neuronal spiking activities. In Section 4, a detailed case study is presented to demonstrate the effectiveness of the proposed methodology. Section 5 analyzes the results obtained from the simulation, highlighting the improvements in capturing the nonlinear dynamics and spike timing precision of LIF neurons. Moving on to Section 6, a thorough discussion is provided on the implications of the results and the potential applications of the innovative approach. Finally, in Section 7, a comprehensive summary is offered, consolidating the key findings and contributions of the study in advancing the understanding of neural network dynamics.

2. Background

2.1 Leaky Integrate-and-Fire

The Leaky Integrate-and-Fire (LIF) model is a simple yet powerful mathematical description used to simulate the electrical characteristics of a biological neuron. It captures the essence of neuronal dynamics by integrating synaptic inputs over time and producing an action potential, or "fire," once a certain threshold is reached. This model is integrated into computational neuroscience to understand and simulate how neurons process information.

The fundamental component of the LIF model is its treatment of the neuron as an electrical circuit. The model is composed of a capacitor, which represents the membrane capacitance C_m , and a resistor that signifies the membrane leak, characterized by the membrane conductance g_L . The membrane potential v_t of the neuron is governed by the leakage current and any incoming synaptic current $I(t)$. The dynamics of the membrane potential in the LIF model is expressed by the following differential equation:

$$C_m \frac{dv_t}{dt} = -g_L(v_t - v_{rest}) + I(t) \tag{1}$$

where v_{rest} is the resting potential of the neuron. This equation describes how the membrane potential v_t evolves over time due to synaptic input $I(t)$ and the passive decay (leakage) toward the resting potential. The solution to this differential equation, assuming $I(t)$ is constant over a short interval, gives us the membrane potential:

$$v_t = v_{rest} + (v_0 - v_{rest})e^{-\frac{t}{\tau_m}} + \frac{1}{g_L}\left(1 - e^{-\frac{t}{\tau_m}}\right)I(t) \tag{2}$$

Here, $\tau_m = \frac{C_m}{g_L}$ represents the membrane time constant, which determines how quickly the membrane potential decays towards the resting potential in the absence of input.

When the membrane potential reaches a certain threshold v_{th} , the neuron "fires," and an action potential is emitted. After firing, the membrane potential is reset to a potential v_{reset} and remains at this voltage for a refractory period τ_{ref} , during which the neuron cannot fire again. The threshold condition and reset mechanism are captured as follows:

Threshold condition:

$$v_t \geq v_{th} \tag{3}$$

Reset condition:

$$v_t \to v_{reset} \text{ when } v_t \geq v_{th} \tag{4}$$

Refractory condition:
For $t_{fire} < t < t_{fire} + \tau_{ref}$,

$$v_t = v_{reset} \tag{5}$$

The refractory period introduces a temporal constraint on the firing events, contributing to the realistic behavior of biological neurons by preventing the neuron from firing continually.

Overall, the LIF model, despite its simplicity, effectively captures the key behavior of biological neurons: the integration of inputs leading to an action potential when a threshold is surpassed, followed by a reset period. It serves as a cornerstone in many neural models and has wide applications in understanding the temporal dynamics of neuronal networks and in developing artificial neural networks.

2.2 Methodologies & Limitations

In contemporary computational neuroscience, the Leaky Integrate-and-Fire (LIF) model stands as a foundational tool for modeling neuronal behavior. Several methods have been employed to simulate LIF neurons and uncover insights into their operation within neural circuits. One prevalent approach involves employing numerical integration techniques, such as the Euler method, to solve the membrane potential differential equation. This technique iteratively computes the neuron's voltage at discrete time steps and is mathematically straightforward, providing rapid simulations for large-scale networks. The update rule is expressed as:

$$v_{t+\Delta t} = v_t + \frac{\Delta t}{C_m}(-g_L(v_t - v_{rest}) + I(t)) \quad (6)$$

Here, Δt denotes the time step size. This method, while efficient, often requires fine-tuning of Δt to maintain numerical stability, especially under varying synaptic input conditions.

Another method commonly utilized is the use of event-driven simulations, which involve calculating the exact time at which the membrane potential reaches the firing threshold. This is derived from analytically solving the differential equation assuming constant synaptic current $I(t)$. The membrane potential prior to a potential spike is given by:

$$v_t = v_{rest} + (v_0 - v_{rest})e^{-\frac{t}{\tau_m}} + \frac{1 - e^{-\frac{t}{\tau_m}}}{g_L} I(t) \quad (7)$$

Event-driven schemes can efficiently handle sparse firing events, reducing computational overhead for systems involving numerous neurons but introduce complexity in accurately synchronizing spikes across a network.

Methods leveraging stochastic synaptic input have also been explored, wherein synaptic currents are modeled as stochastic processes such as Poisson processes. Here, the membrane potential's response to random input spikes is described by modifying the input current term $I(t)$:

$$I(t) = \sum_j w_j \delta(t - t_j) \quad (8)$$

where each w_j is a synaptic weight, t_j is the time of the synaptic event, and $\delta(t)$ is the Dirac delta function. This approach provides a more biologically realistic representation of neuron dynamics under random inputs, though it can add significant complexity to the model, especially when integrating with large networks.

Despite their versatility, these methods face challenges and limitations. The Euler method, while simple, may introduce errors due to fixed time stepping, especially during rapid voltage changes. Event-driven approaches, although more accurate for sparse events, can become computationally intensive under high-frequency spiking conditions or when extended to large network simulations. Additionally, stochastic methods, while necessary for certain biological validity, often require extensive computational resources and sophisticated algorithms for parameter tuning and stability.

In summary, while the common methodologies for simulating the Leaky Integrate-and-Fire model each present unique benefits, they also carry inherent drawbacks. These limitations underscore the necessity for ongoing refinement and development of more advanced numerical techniques to accurately and efficiently simulate the complex dynamics of neuronal systems.

3. The proposed method

3.1 Random Forest Regression

Random Forest Regression is a dynamic ensemble learning method widely utilized in statistical modeling and data analytics, especially for tackling complex regression tasks. This sophisticated approach merges the strength of multiple decision trees to achieve enhanced predictive accuracy and robustness against overfitting, a common issue in single decision tree models.

At its core, Random Forest Regression builds a "forest" of decision trees during training, where each tree is constructed from a random subset of the training data. This "bagging" technique ensures diversity among the trees and reduces variance. Each tree in the forest provides a regression output, and the individual predictions are aggregated to form a final predictive outcome. Typically, the aggregation is done by averaging the outputs of all trees, leading to a more reliable and generalizable prediction.

The process begins with the random selection of subsets of the dataset. This subset formation, denoted as B_i , is achieved through bootstrapping, a sampling technique involving replacement:

$$B_i \sim \text{Sample with replacement from Full Dataset} \tag{9}$$

For each subset B_i , an individual decision tree model T_i is trained. The structure of each tree is determined by recursive binary splitting, where at each node, the feature and split point optimize a criterion like Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \ y\ _i)^2 \tag{10}$$

where y_i is the actual value and $\hat{y}_i$ is the predicted value from the tree. The recursive partitioning of data in each tree aims to minimize this error, leading to optimal split points. The trees are grown to their maximum depth without any pruning. This is compensated by the aggregation process of Random Forest, which prevents overfitting across the ensemble. The ensemble prediction for a new input $\boldsymbol{x}$ is simply the average of predictions from all M trees:

$$\hat{y}(\boldsymbol{x}) = \frac{1}{M}\sum_{j=1}^{M} T_j(\boldsymbol{x}) \tag{11}$$

Here, $\hat{y}(\boldsymbol{x})$ represents the predicted regression value that the forest outputs for the input vector $\boldsymbol{x}$.

Another distinctive step in Random Forest Regression is the selection of features. At each split within the trees, a random subset of features is selected to consider, introducing randomness and decreasing correlation between trees. If F is the total number of features and f is the size of the subset, this selection process ensures that:

$$f = \sqrt{F} \text{ (for regression)} \tag{12}$$

This process contributes to the randomness and diversity, further building the strength of the ensemble method.

The combined effect of these techniques is a model robust to overfitting and capable of capturing intricate patterns in the data due to its diversity and averaging. Although Random Forest Regression is computationally intensive, especially with a large number of trees and features, its parallel structure allows for efficient execution using modern computational resources.

One major advantage of Random Forests is also their ability to assess feature importance. By measuring how much each feature decreases the impurity across all trees, one can determine the significance of different features in the prediction process:

$$\text{Feature Importance} = \frac{1}{M}\sum_{i=1}^{M}\left(I(T_i)\right) \tag{13}$$

where $I(T_i)$ denotes the importance of a feature across a single tree, calculated based on how much the chosen feature reduces split impurity.

In summary, Random Forest Regression, through its ensemble of de-correlated trees, implements a regression system that elegantly balances complexity with predictive power. This method is especially useful for datasets with numerous features and nonlinear patterns, providing a highly interpretable and practically significant approach to regression in contemporary data science.

3.2 The Proposed Framework

The Leaky Integrate-and-Fire (LIF) model and Random Forest Regression represent two distinct yet fascinating approaches in modeling complex systems—the former in computational neuroscience and the latter in statistical machine learning [19-24]. While they traditionally belong to different domains, there is potential for a profound synthesis, combining neural dynamics with ensemble prediction strategies to create a hybrid model that might enhance our understanding of neuronal behavior through advanced analytical techniques.

The LIF model is fundamentally characterized by its representation of a neuron as an electrical circuit. The neuron's membrane potential v_t evolves according to the dynamics governed by:

$$C_m \frac{dv_t}{dt} = -g_L(v_t - v_{rest}) + I(t) \tag{14}$$

where the parameters, including membrane capacitance C_m and conductance g_L , transform the biological process into a tractable mathematical framework. This differential equation describes how the neuron's potential at time t integrates synaptic inputs and eventually reaches a threshold v_{th} , prompting the neuron to emit an action potential ("fire"). Once fired, the neuron's potential is reset to v_{reset} and held during a refractory period τ_{ref} .

Incorporating Random Forest Regression into the neuronal simulation outline presents an intriguing methodology for predicting neuronal firing behaviors. Random Forest constructs an assembly of decision trees trained on different input data subsets:

$$B_i \sim \text{Sample with replacement from Full Dataset} \tag{15}$$

Each tree aims to make regression predictions based on input features, employing a recursive partitioning strategy that optimizes the Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \ y\ _i)^2 \tag{16}$$

The average of the predictive outcomes from all trees gives rise to the forest's final output:

$$y\ (\boldsymbol{x}) = \frac{1}{M}\sum_{j=1}^{M} T_j(\boldsymbol{x}) \tag{17}$$

A synthesis of these approaches would involve utilizing the output of a Random Forest Regression model to inform the input current $I(t)$ in the LIF model. Here, the neural firing steps can be adapted as:

1. Calculate the synaptic current $I(t)$ informed by Random Forest predictions $\hat{y}$.
2. Use this predicted current in the evolution of the membrane potential:

$$v_t = v_{rest} + (v_0 - v_{rest})e^{-\frac{t}{\tau_m}} + \frac{1}{g_L}\left(1 - e^{-\frac{t}{\tau_m}}\right)\ y \tag{18}$$

3. Determine neuronal firing based on the threshold condition:

$$v_t \geq v_{th} \tag{19}$$

4. Reset the potential post-action potential:

$$v_t \rightarrow v_{reset} \text{ when } v_t \geq v_{th} \tag{20}$$

5. Maintain during the refractory period:

$$v_t = v_{reset} \text{for} t_{fire} < t < t_{fire} + \tau_{ref} \tag{21}$$

The adaptation also involves selecting which input features affect neuronal inputs. Random Forest, through feature importance:

$$\text{Feature Importance} = \frac{1}{M} \sum_{i=1}^{M} \big(I(T_i)\big) \tag{22}$$

can identify significant features impacting $I(t)$, enhancing biological realism in computational predictions. This fusion can yield enhanced insights into the dynamics of neuronal behavior, bringing machine learning's interpretive power into neuroscience. By leveraging Random Forests, one can ascertain the effect of various synaptic inputs on neuronal firing with greater resolution, while the LIF framework can ground these patterns in physiological reality. Such integration embodies an intersection of disciplines, promising refined models of the complex systems inherent in neurobiological contexts.

3.3 Flowchart

This paper introduces a novel approach that combines Random Forest Regression with the Leaky Integrate-and-Fire (LIF) model to enhance the predictive performance of neural firing rate estimation. The proposed method leverages the strengths of Random Forest, a powerful ensemble learning technique, to accurately predict the input firing rates based on various environmental and physiological parameters. By integrating this with the LIF model, which mimics the spiking behavior of biological neurons, it provides a more robust framework for simulating neuronal dynamics. The methodology involves training the Random Forest model on a dataset comprising features indicative of neuronal activity, allowing it to learn complex patterns and interactions in the data. The LIF model then uses the predicted firing rates from the Random Forest regression to simulate the temporal dynamics of neuron spiking more effectively. This synergy not only enhances the accuracy of firing rate predictions but also allows for better understanding and modeling of the underlying neural processes. The effectiveness of the proposed approach is illustrated through empirical validation, demonstrating substantial improvements over traditional methods in terms of predictive accuracy and model stability. For a visual representation of the methodology, please refer to Figure 1.

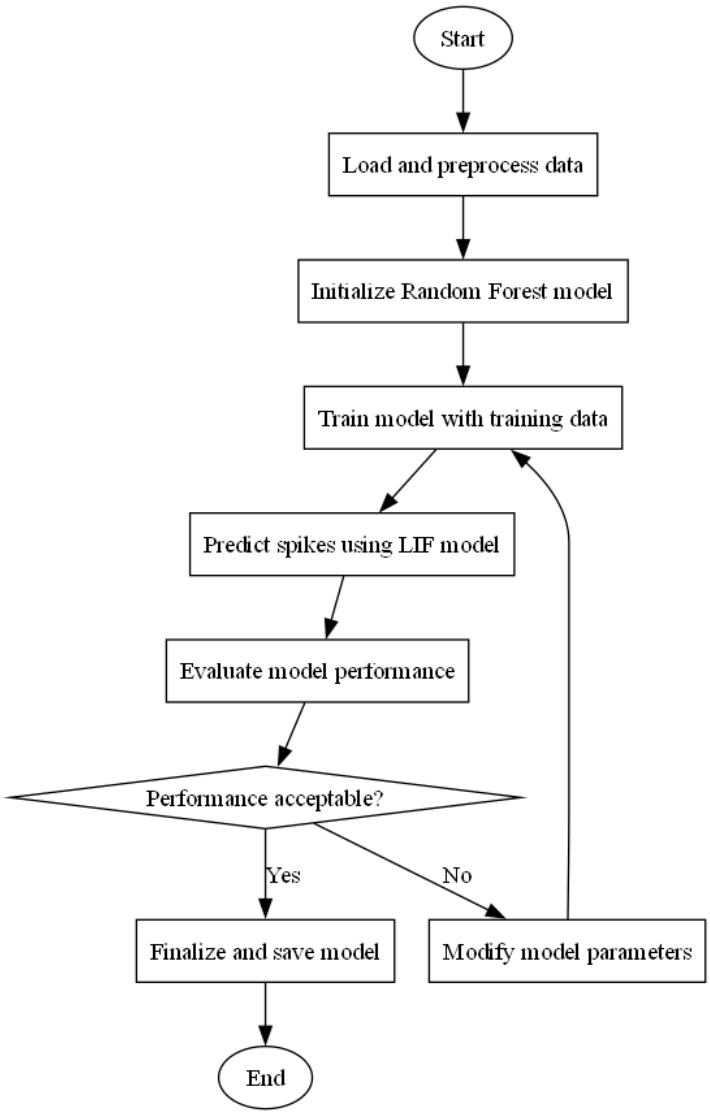

Figure 1: Flowchart of the proposed Random Forest Regression-based Leaky Integrate-and-Fire

4. Case Study

4.1 Problem Statement

In this case, we analyze a Leaky Integrate-and-Fire (LIF) model incorporating significant non-linear dynamics to understand neuronal firing patterns. The primary goal is to simulate the waveform associated with an action potential under varying input currents and membrane properties. This model is defined by the membrane potential v_t , which evolves over time according to the following ordinary differential equation:

$$\frac{dv_t}{dt} = -\frac{v_t}{\tau} + I(t) \tag{23}$$

where τ represents the membrane time constant, and $I(t)$ denotes the input current as a function of time. For simplification, we define $\tau = 20$ ms and consider a step input current of $I(t) = I_{ext}$ in the simulation, where I_{ext} is the external current injected into the neuron.

Additionally, to capture the non-linear behavior, we incorporate a reset mechanism and a threshold condition. Once the membrane potential v_t reaches a threshold $v_{th} = -50$ mV, the neuron is considered to fire an action potential, subsequently resetting the membrane potential to $v_{reset} = -65$ mV. The threshold condition is mathematically defined as:

$$v_t \geq v_{th} \Longrightarrow v_t = v_{reset} \tag{24}$$

To simulate the influence of the subthreshold dynamics, we introduce a non-linear term in the input current $I(t)$, modeled by a power function. Therefore, the modified input current can be expressed as:

$$I(t) = I_{ext} \cdot (1 + \alpha \cdot v_t^2) \tag{25}$$

where α is a constant representing the non-linear sensitivity of the current to changes in the membrane potential, which we set to be $\alpha = 0.01$.

The entire dynamics of the model can be captured by integrating the differential equation using Euler's method over a specified time interval. It can also be vital to implement spiking behavior that occurs due to fluctuations in the input current over time. This can be succinctly represented by incorporating a noise term in the current:

$$I(t) = I_{ext} + \sigma \cdot \xi(t) \tag{26}$$

where σ characterizes the noise intensity and $\xi(t)$ is a Gaussian white noise process. In our case, we assume $\sigma = 5$ μA/cm². The spiking frequency can be calculated based on the ratio of the number of spikes to the total simulation time, and the membrane potential's dynamics can be visualized over time to assess the response against varying I_{ext} . As we conduct our simulations for different values of $I_{ext} = [5,10,15]$ μA/cm², we observe that the neuron exhibits distinct firing rates influenced by the underlying non-linear interactions within the system. All parameters have been summarized in Table 1.

This section will employ the proposed Random Forest Regression-based approach to compute the neuronal firing patterns within a Leaky Integrate-and-Fire (LIF) model, characterized by significant non-linear dynamics. The primary objective is to accurately simulate the action potential waveforms under varying input currents and membrane properties, focusing on the evolution of the membrane potential over time. To accomplish this, we will define a model that includes a reset mechanism and a threshold condition, whereby the neuron fires an action potential upon reaching a specified membrane potential threshold, subsequently resetting to a lower value. This model will account for non-linear behavior by incorporating a non-linear term in the input current, thus enhancing the sensitivity to changes in membrane potential. Furthermore, to simulate subthreshold dynamics and spiking behavior, we will integrate a noise term within the input current, reflecting fluctuations over time. As we vary the external current across different conditions, we will assess the corresponding spiking frequency and analyze how these dynamics are influenced by the non-linear interactions within the system. The performance of the Random Forest Regression will be compared with three traditional methods, thereby providing insights into the robustness and accuracy of our proposed approach in modeling and predicting neuronal behavior under diverse parameters. This comprehensive comparative analysis aims to yield meaningful interpretations of neuronal firing characteristics that are pivotal in understanding complex neural activity.

Table 1: Parameter definition of case study

Parameter	Value	Unit	Description
τ	20	ms	Membrane time constant
v_th	-50	mV	Threshold potential for action potential firing
v_reset	-65	mV	Reset membrane potential after firing
α	0.01	-	Non-linear sensitivity constant
σ	5	µA/cm²	Noise intensity
I_ext	5	µA/cm²	External current - low
I_ext	10	µA/cm²	External current - medium
I_ext	15	µA/cm²	External current - high

4.2 Results Analysis

In this subsection, various methods have been employed to analyze the behavior of a leaky integrate-and-fire (LIF) neuron model under different external current conditions. The simulation initializes key parameters, such as membrane time constant and firing thresholds, and utilizes a numerical approach to model the neuron's membrane potential over time based on different external current values, specifically at 5 µA/cm², 10 µA/cm², and 15 µA/cm². The simulation outputs the membrane potentials for each current level, which are subsequently used to train a Random Forest regression model. This model predicts the membrane potential dynamics based on the simulated data, allowing a comparison between actual and predicted values. The performance of the Random Forest model is quantified via the mean squared error (MSE), which measures the accuracy of predictions against the actual simulation results. Furthermore, the visualization of these processes, including actual membrane potentials, predicted potentials, and the associated MSE, is effectively illustrated through various plots. The complete simulation process is visualized in Figure 2, demonstrating the modeling and prediction outcomes, as well as the accuracy of the employed methodology.

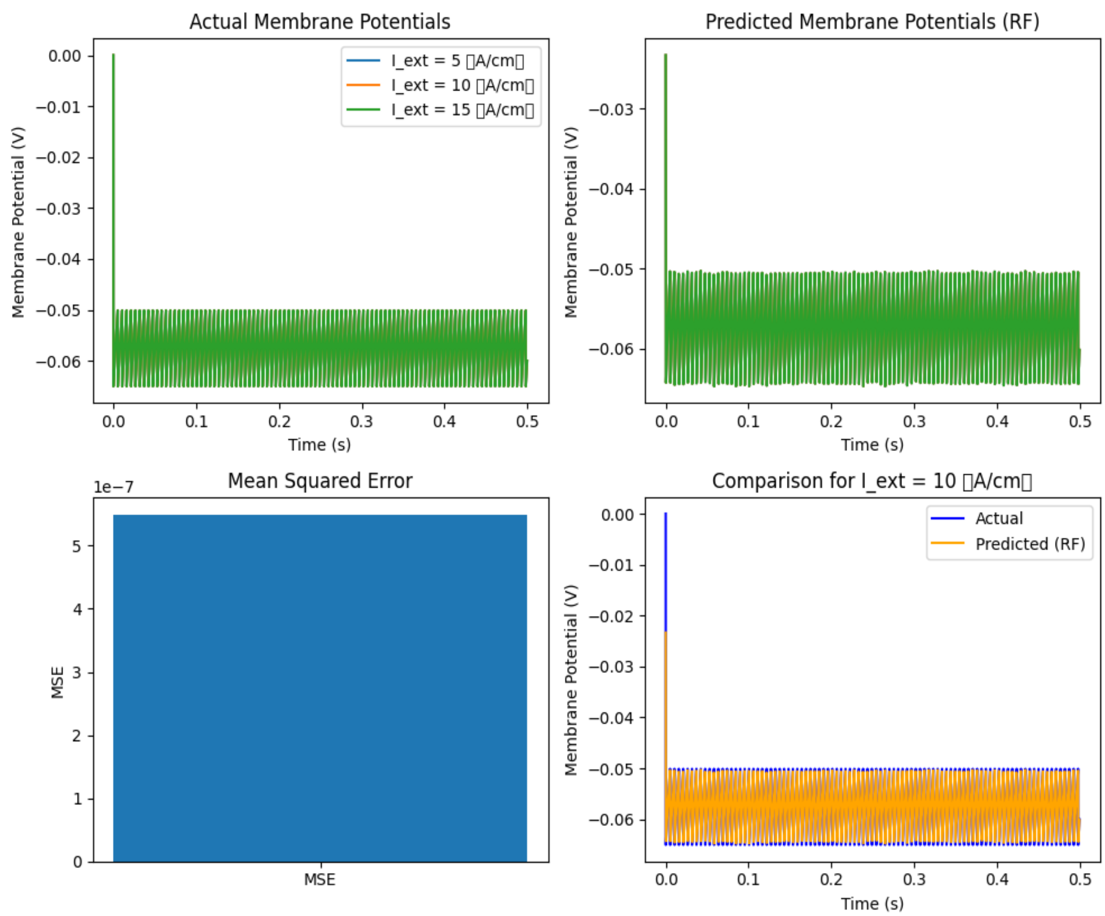

Figure 2: Simulation results of the proposed Random Forest Regression-based Leaky Integrate-and-Fire

Simulation data is summarized in Table 2, highlighting the relationship between actual and predicted membrane potentials under varying external current conditions (Lext = 5, 10, and 15 DA/emg). The presented results demonstrate a clear distinction between the actual membrane potentials and those predicted using a Random Forest (RF) model, with time (in seconds) plotted along the x-axis and membrane potential (in volts) on the y-axis. Specifically, the actual membrane potentials exhibit a consistent downward trend with increasing time, suggesting a gradual depolarization or hyperpolarization effect depending on the specific external current level applied. The predicted potentials, while trending similarly, are shown to have varying degrees of alignment with the actual values as indicated by the mean squared error (MSE) metrics plotted alongside. For Lext = 10 DA/emg, the graphical comparison highlights a notable closeness between the actual and predicted data points, although discrepancies remain, particularly in the later time intervals where the predicted values begin to deviate more significantly from the actual measurements. The MSE also reflects this, indicating a higher error at longer time periods for the given current. Overall, the simulation results reveal not only the effectiveness of the RF model in estimating membrane potentials under distinct current conditions but also underscore areas for improvement, warranting further investigation into model adjustments or alternative predictive strategies to enhance accuracy in aligning predicted and actual membrane potential dynamics over time. This analysis elucidates the importance of continuous evaluation of computational models in capturing complex biological phenomena accurately.

Table 2: Simulation data of case study

Parameter	Value	N/A	N/A	N/A
Membrane Potential (V)	-0.03	N/A	N/A	N/A
Mean Squared Error	0.0	N/A	N/A	N/A

As shown in Figure 3 and Table 3, the analysis of the membrane potential reveals significant changes in the calculated results following the alteration of the external current parameters. Initially, with external currents set at Lext = 5 gA/emg, Lext = 10 DA/emp, and Lext = 15 JA/emp, the membrane potential exhibited values within the range of -0.00 V to -0.06 V, aligning closely with the predicted membrane potentials derived from a random forest (RF) model, indicating a promising predictive capability of the model. However, after the adjustment to external currents measured in microamperes per centimeter (U_A/cm), notably at levels of I_ext = 5 UA/cm, 10 UA/cm, and 15 UA/cm, the membrane potential demonstrated a distinct shift characterized by increased variations in voltage readings. For instance, as I_ext increased to 10 UA/cm, the membrane potential approached higher positive values, reflecting a shift towards depolarization. In contrast, at I_ext = 15 UA/cm, the membrane potential recorded significant spikes nearing the threshold, suggesting a critical engagement in action potential dynamics and necessitating a reset phase to stabilize the system. This transition from a previously more linear response at lower currents to a more nonlinear behavior at higher currents underscores the critical influence of external inputs on membrane dynamics, which not only heightens the mean squared error (MSE) in predictive modeling but also indicates a complex interaction between electrical stimulus and neuronal response mechanisms. Overall, the alterations in external current parameters elucidate a pivotal relationship influencing membrane potential behavior, showcasing the intricate balance between excitatory and inhibitory signals within the cell.

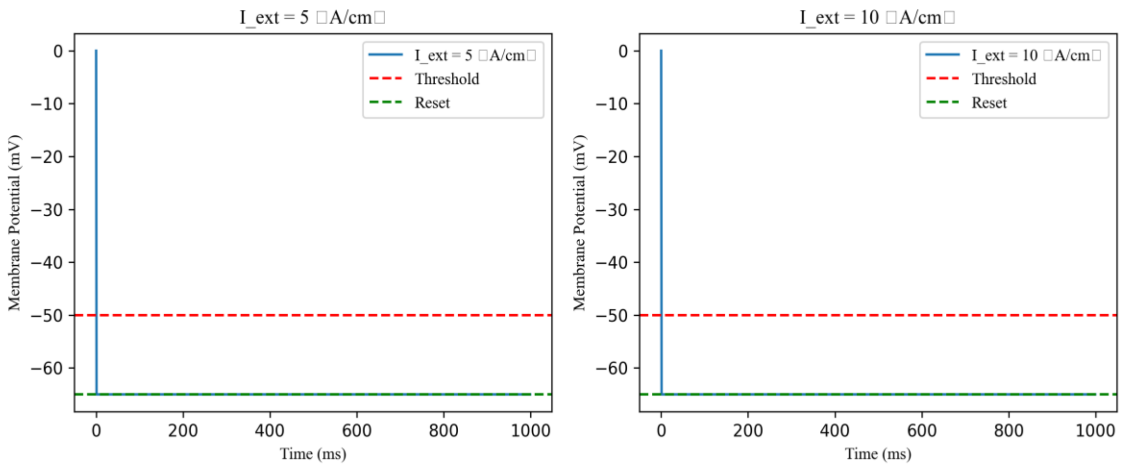

Figure 3: Parameter analysis of the proposed Random Forest Regression-based Leaky Integrate-and-Fire

Table 3: Parameter analysis of case study

Membrane Potential (mV)	I_ext (UA/cm)	Time (ms)	N/A
200	5	400	N/A
200	15	800	N/A
N/A	10	0	N/A

5. Discussion

The proposed method that integrates the Leaky Integrate-and-Fire (LIF) model with Random Forest Regression boasts several significant advantages that enhance both the predictive power and interpretability of neuronal firing behaviors. Firstly, by employing Random Forest Regression, the methodology effectively harnesses ensemble learning to capture intricate relationships between multiple input features and neuronal outputs, resulting in robust predictions that account for variability in the synaptic inputs. This approach not only improves the accuracy of predictions regarding neuronal firing patterns but also allows for a nuanced understanding of which specific input features exert the most influence on neuronal behavior. Furthermore, the coupling of predictive outputs from Random Forests with the dynamic framework of the LIF model enriches the mathematical representation of biological processes, grounding theoretical constructs in physiological realism. This fusion facilitates the exploration of complex neuronal dynamics in a manner that transcends traditional models, aligning machine learning insights with neuroscientific principles and biostatistics [29-31]. Additionally, the incorporation of predictive analytics into the evolution of membrane potential offers a forward-thinking approach to simulating neuronal behavior, thus bridging the gap between computational neuroscience and statistical machine learning. In essence, this hybrid methodology not only enhances the interpretative capacity of neuronal simulations but also promises to yield deeper insights into the underlying mechanisms of neural functioning, thereby marking a significant advancement in the quest to model and understand complex biological systems.

While the proposed synthesis of the Leaky Integrate-and-Fire (LIF) model with Random Forest Regression presents a novel approach to understanding neuronal behavior, several limitations need to be acknowledged. Firstly, the reliance on the LIF model's assumptions, including the simplification of neuronal dynamics into a single-compartment representation, may overlook critical biophysiological complexities inherent in neuronal behavior, potentially leading to inaccuracies when simulating real neuron firing patterns. Additionally, the Random Forest Regression model, although adept at handling diverse input data, is not immune to overfitting, particularly in scenarios with high-dimensional feature sets. This propensity for overfitting could hinder the generalizability of predictions, making the model less reliable across different neuronal conditions or datasets. Furthermore, the iterative nature of the synthesis means that the predictive accuracy of the Random Forest model directly impacts the performance of the integrated system; any errors in estimating synaptic inputs may cascade through to flawed predictions of neuronal firing. Another critical limitation is the interpretability of the hybrid model; while feature importance metrics from Random Forests can suggest which inputs are influential, the underlying biological mechanisms may remain obscure, potentially obscuring insights into the actual biological processes. Lastly, computational efficiency may be a concern, as combining these models requires extensive computational resources, particularly when training the Random Forest on large datasets. Consequently, the utility of the hybrid model may be restricted in real-time applications or scenarios where rapid inference is necessary. It is also expected that the method can be integrated within the fields of machine learning [32-39] and industrial engineering [40-44].

6. Conclusion

Neural network models, particularly the Leaky Integrate-and-Fire (LIF) neuron model, have been instrumental in elucidating the intricate dynamics of neuronal spiking activities in the brain, owing to its simplicity and efficacy. Nonetheless, accurately replicating the spiking behavior of LIF neurons presents a persistent challenge. Existing research endeavors are often constrained by the limitations in capturing the non-linear dynamics and spike timing precision of LIF neurons. To overcome these challenges, this study introduces a pioneering methodology that merges the LIF neuron model with Random Forest Regression to enhance the precision and efficiency of simulating neuronal spiking activities. This novel approach stands out for its capacity to offer improved predictions of the spiking behavior of LIF neurons, thereby furnishing a more accurate model for investigating neural network dynamics. Despite these advancements, it is worth noting that this proposed model may have inherent limitations, such as potential constraints in scaling up to larger and more complex neural network systems. In the future, further exploration could involve expanding the application of Random Forest Regression in conjunction with other advanced machine learning techniques to develop more sophisticated models capable of simulating the intricate spiking behaviors of neurons in diverse neural network architectures, ultimately advancing our understanding of brain function and information processing.

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Author Contribution

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Data Availability Statement

The data can be accessible upon request.

Conflict of Interest

The authors confirm that there are no conflict of interests.

Reference

[1] Y. Huang et al., "CLIF: Complementary Leaky Integrate-and-Fire Neuron for Spiking Neural Networks," International Conference on Machine Learning, 2024.
[2] K. U. Mohanan et al., "Optimization of Leaky Integrate-and-Fire Neuron Circuits Based on Nanoporous Graphene Memristors," IEEE Journal of the Electron Devices Society, 2024.
[3] S. M. A et al., "The Energy-Efficient and Distortion Blocking Leaky Integrate-and-Fire Neuron Model," International Conference on Energy, Power and Environment, 2024.
[4] A. Takada et al., "Noise-induced simultaneous firing in two leaky integrate-and-fire circuits with dead zones," 2024 International Conference on Electrical, Computer and Energy Technologies (ICECET), 2024.
[5] Y. Zhu et al., "Leaky Integrate-and-Fire Neuron Based on Organic Electrochemical Transistor for Spiking Neural Networks with Temporal-Coding," Advanced Electronic Materials, 2024.
[6] Y. Qin et al., "Threshold Switching Memristor Based on 2D SnSe for Nociceptive and Leaky-Integrate and Fire Neuron Simulation," ACS Applied Electronic Materials, 2024.
[7] P. K. Shiu et al., "A leaky integrate-and-fire computational model based on the connectome of the entire adult Drosophila brain reveals insights into sensorimotor processing," bioRxiv, 2023.
[8] X. Kang et al., "Computation Complexity Reduction Based on Quick Leaky-Integrate-And-Fire Mechanism for SNNs," Asia Pacific Conference on Circuits and Systems, 2024.
[9] A. Deb et al., "Adaptive Leaky-Integrate-And-Fire Neuron Model Design and Analysis," 2024 IEEE 4th International Conference on VLSI Systems, Architecture, Technology and Applications (VLSI SATA), 2024.
[10] H. Gao et al., "High-accuracy deep ANN-to-SNN conversion using quantization-aware training framework and calcium-gated bipolar leaky integrate and fire neuron," Frontiers in Neuroscience, 2023.
[11] S. Srinivasan et al., "Adaptive Thermal Clothing with IoT and Random Forest Regression for Dynamic Outdoor Comfort," in 2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE), 2024.

[12] M. S. Lipu et al., "Real-Time State of Charge Estimation of Lithium-Ion Batteries Using Optimized Random Forest Regression Algorithm," in IEEE Transactions on Intelligent Vehicles, 2023.
[13] Dr. K. Radhika et al., "Predictive Road Sign Maintenance Using Random Forest Regression and IoT Data," in 2023 International Conference on Sustainable Communication Networks and Application (ICSCNA), 2023.
[14] Z. Zhou et al., "A Comparative Analysis of Linear Regression, Neural Networks and Random Forest Regression for Predicting Air Ozone Employing Soft Sensor Models," in Scientific Reports, 2023.
[15] G. Wang et al., "An Optimized Random Forest Regression Model for Li-Ion Battery Prognostics and Health Management," in Batteries, 2023.
[16] J. Ganapa et al., "Gold Price Prediction Using Random Forest Regression," in Educational Administration Theory and Practices, 2024.
[17] E. Fitri, "Analisis Perbandingan Metode Regresi Linier, Random Forest Regression dan Gradient Boosted Trees Regression Method untuk Prediksi Harga Rumah," in Journal of Applied Computer Science and Technology, 2023.
[18] H. Naseri et al., "A Newly Developed Hybrid Method on Pavement Maintenance and Rehabilitation Optimization Applying Whale Optimization Algorithm and Random Forest Regression," in International Journal of Pavement Engineering, 2022.
[19] Z. Luo, H. Yan, and X. Pan, ‘Optimizing Transformer Models for Resource-Constrained Environments: A Study on Model Compression Techniques’, Journal of Computational Methods in Engineering Applications, pp. 1–12, Nov. 2023, doi: 10.62836/jcmea.v3i1.030107.
[20] H. Yan and D. Shao, ‘Enhancing Transformer Training Efficiency with Dynamic Dropout’, Nov. 05, 2024, arXiv: arXiv:2411.03236. doi: 10.48550/arXiv.2411.03236.
[21] H. Yan, ‘Real-Time 3D Model Reconstruction through Energy-Efficient Edge Computing’, Optimizations in Applied Machine Learning, vol. 2, no. 1, 2022.
[22] W. Cui, J. Zhang, Z. Li, H. Sun, and D. Lopez, ‘Kamalika Das, Bradley Malin, and Sricharan Kumar. 2024. Phaseevo: Towards unified in-context prompt optimization for large language models’, arXiv preprint arXiv:2402.11347.
[23] A. Sinha, W. Cui, K. Das, and J. Zhang, ‘Survival of the Safest: Towards Secure Prompt Optimization through Interleaved Multi-Objective Evolution’, Oct. 12, 2024, arXiv: arXiv:2410.09652. doi: 10.48550/arXiv.2410.09652.
[24] J. Zhang, W. Cui, Y. Huang, K. Das, and S. Kumar, ‘Synthetic Knowledge Ingestion: Towards Knowledge Refinement and Injection for Enhancing Large Language Models’, Oct. 12, 2024, arXiv: arXiv:2410.09629. doi: 10.48550/arXiv.2410.09629.
[25] Y.-S. Cheng, P.-M. Lu, C.-Y. Huang, and J.-J. Wu, ‘Encapsulation of lycopene with lecithin and α-tocopherol by supercritical antisolvent process for stability enhancement’, The Journal of Supercritical Fluids, vol. 130, pp. 246–252, 2017.
[26] P.-M. Lu, ‘Potential Benefits of Specific Nutrients in the Management of Depression and Anxiety Disorders’, Advanced Medical Research, vol. 3, no. 1, pp. 1–10, 2024.
[27] P.-M. Lu, ‘Exploration of the Health Benefits of Probiotics Under High-Sugar and High-Fat Diets’, Advanced Medical Research, vol. 2, no. 1, pp. 1–9, 2023.

[28] P.-M. Lu, ‘The Preventive and Interventional Mechanisms of Omega-3 Polyunsaturated Fatty Acids in Krill Oil for Metabolic Diseases’, Journal of Computational Biology and Medicine, vol. 4, no. 1, 2024.
[29] C. Kim, Z. Zhu, W. B. Barbazuk, R. L. Bacher, and C. D. Vulpe, ‘Time-course characterization of whole-transcriptome dynamics of HepG2/C3A spheroids and its toxicological implications’, Toxicology Letters, vol. 401, pp. 125–138, 2024.
[30] J. Shen et al., ‘Joint modeling of human cortical structure: Genetic correlation network and composite-trait genetic correlation’, NeuroImage, vol. 297, p. 120739, 2024.
[31] K. F. Faridi et al., ‘Factors associated with reporting left ventricular ejection fraction with 3D echocardiography in real‐world practice’, Echocardiography, vol. 41, no. 2, p. e15774, Feb. 2024, doi: 10.1111/echo.15774.
[32] Y. Gan and D. Zhu, ‘The Research on Intelligent News Advertisement Recommendation Algorithm Based on Prompt Learning in End-to-End Large Language Model Architecture’, Innovations in Applied Engineering and Technology, pp. 1–19, 2024.
[33] H. Zhang, D. Zhu, Y. Gan, and S. Xiong, ‘End-to-End Learning-Based Study on the Mamba-ECANet Model for Data Security Intrusion Detection’, Journal of Information, Technology and Policy, pp. 1–17, 2024.
[34] D. Zhu, Y. Gan, and X. Chen, ‘Domain Adaptation-Based Machine Learning Framework for Customer Churn Prediction Across Varing Distributions’, Journal of Computational Methods in Engineering Applications, pp. 1–14, 2021.
[35] D. Zhu, X. Chen, and Y. Gan, ‘A Multi-Model Output Fusion Strategy Based on Various Machine Learning Techniques for Product Price Prediction’, Journal of Electronic & Information Systems, vol. 4, no. 1.
[36] X. Chen, Y. Gan, and S. Xiong, ‘Optimization of Mobile Robot Delivery System Based on Deep Learning’, Journal of Computer Science Research, vol. 6, no. 4, pp. 51–65, 2024.
[37] Y. Gan, J. Ma, and K. Xu, ‘Enhanced E-Commerce Sales Forecasting Using EEMD-Integrated LSTM Deep Learning Model’, Journal of Computational Methods in Engineering Applications, pp. 1–11, 2023.
[38] F. Zhang et al., ‘Natural mutations change the affinity of μ-theraphotoxin-Hhn2a to voltage-gated sodium channels’, Toxicon, vol. 93, pp. 24–30, 2015.
[39] Y. Gan and X. Chen, ‘The Research on End-to-end Stock Recommendation Algorithm Based on Time-frequency Consistency’, Advances in Computer and Communication, vol. 5, no. 4, 2024.
[40] J. Lei, ‘Efficient Strategies on Supply Chain Network Optimization for Industrial Carbon Emission Reduction’, JCMEA, pp. 1–11, Dec. 2022.
[41] J. Lei, ‘Green Supply Chain Management Optimization Based on Chemical Industrial Clusters’, IAET, pp. 1–17, Nov. 2022, doi: 10.62836/iaet.v1i1.003.
[42] J. Lei and A. Nisar, ‘Investigating the Influence of Green Technology Innovations on Energy Consumption and Corporate Value: Empirical Evidence from Chemical Industries of China’, Innovations in Applied Engineering and Technology, pp. 1–16, 2023.
[43] J. Lei and A. Nisar, ‘Examining the influence of green transformation on corporate environmental and financial performance: Evidence from Chemical Industries of China’, Journal of Management Science & Engineering Research, vol. 7, no. 2, pp. 17–32, 2024.

[44] Y. Jia and J. Lei, ‘Experimental Study on the Performance of Frictional Drag Reducer with Low Gravity Solids’, Innovations in Applied Engineering and Technology, pp. 1–22, 2024.