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Fractional Calculus-Based Modeling for Intelligent Healthcare Prediction Systems

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Abstract- — Early-stage hiring processes continue to depend on resume-based and keyword-based filtering, which does not reliably capture a candidate's actual abilities. This paper presents an AI-assisted skill evaluation system that prioritizes demonstrated performance over resume content. The system models candidate screening as a multi-stage pipeline: skill profiling, dynamic assessment delivery, automated rule-based and NLP evaluation, and weighted score aggregation. A competency model maps candidate skills to standardized assessment criteria, enabling objective cross-candidate comparison. Evaluation on simulated data (n=100) yields a Spearman rank correlation of 0.91, a false-positive shortlist rate of 12%, and a top-quintile precision of 78% — all substantially better than a conventional ATS baseline. The proposed framework is scalable, modular, and designed to reduce bias inherent in resume-centric screening.

Keywords—skill-based evaluation, automated candidate screening, competency model, natural language processing, recruitment pipeline, AI hiring, applicant tracking systems.

I. INTRODUCTION

The fast evolution of smart health care systems has resulted in huge amounts of patients' data, which is a chance but also brings challenges for disease prediction, detection, and therapy [1]. The contemporary health care system uses a range of devices that monitor the continuous physiological activity in intensive care units, or the cardiac rhythms using wearable equipment [2]. Modern systems create data in the form of time series with highly complicated dynamics not captured properly by conventional models based on integer-order derivatives [3]. Standard health care prediction models are based on integer-order differential equations and machine learning techniques [4]. Although widely used, these models have limitations and do not work properly with biological systems that demonstrate complicated dynamics due to the existence of non-local processes in these systems [5]. Such non-locality can be observed in many physiological processes, such as neural signals transfer, decay of drugs concentrations, and cardiac rhythm control [6].

Fractional calculus—generalizing differentiation and integration to non-integer order—is a promising approach to describing memory-related phenomena [7]. As opposed to integer-order derivatives, which describe only the local behavior of functions, fractional-order derivatives consider their global properties, thus incorporating memory effects into the model. The use of a fractional-order parameter introduces a new dimension, making it possible to construct models that correspond to data characteristics [8].

The application of fractional calculus in artificial intelligence opens up new horizons in the field of intelligent healthcare prediction [9]. Fractional-Order Neural Networks (FONNs) represent a novel class of neural networks where integer-order activation dynamics is replaced with fractional-order activation dynamics, providing enhanced learning capabilities for memory-dependent patterns. It was shown that the number of neurons required to perform specific functions and the computing complexity could be substantially lower than for integer-order networks. In addition, fractional-order variants of recurrent networks, such as Fractional-Order Recurrent Neural Networks (FORNNs) and Fractional-Order Long Short-Term Memory (FOLSTM) networks, demonstrated superior performance when dealing with long-term dependencies in time series prediction tasks [10].

This considers the use of fractional calculus in healthcare prediction using intelligent systems in the following manner: (1) a complete theoretical formulation for the use of fractional-order neural networks on healthcare time-series; (2) designing fractional-order long-short term memory networks for the purpose of cardiac arrhythmia classification from ECGs; (3) performance comparison between fractional order versus integer order models; (4) efficiency and representation analysis; and (5) implementation issues in using fractional models in healthcare.

II. LITERATURE SURVEY

Research on the application of fractional calculus in computational intelligence and health care covers a wide range from theoretical fundamentals to practical implementations.

Fundamentals of Fractional Calculus

Fractional calculus is an extension of conventional calculus that applies to fractional orders. It was first introduced by the correspondence of Leibniz and L'Hôpital in 1695. There are three main definitions used for fractional calculus: Riemann-Liouville, Caputo, and Grünwald-Letnikov derivatives. The Caputo form of fractional calculus, which supports integer order initial conditions, has been particularly useful in engineering and biological studies. For a function f(t), the Caputo fractional derivative of order α ($0 < \alpha < 1$) is defined as:

$$ {}^{C}D^{\alpha} f(t) = 1/\Gamma(1-\alpha) \int_0^t f'(\tau)/(t-\tau)^{\alpha} \, d\tau $$

The factor $(t-\tau)^{-\alpha}$ shows that the derivative takes into account the memory of the function, which memory decreases according to the power law. Such nonlocality is the origin of the capacity of fractional calculus in describing phenomena where memory plays a role.

Fractional-Order Neural Networks

FONNs were developed with the aim of exploiting the advantages of fractional-order derivatives. A systematic study on FONNs and their applications by scholars from the University of Tabriz and Islamic Azad University analyzed 65 primary sources related to such topic.

The key conclusions drawn from the literature review include the ability of FONNs to model more complex dynamics, have fewer neurons, be less computationally expensive, and provide increased stability. Slowing down the learning process using fractional-order derivatives reduces the risk of overfitting while retaining the ability to generalize. Another advantage of FONNs is an extra hyperparameter that can be used to enhance network performance, namely the fractional order value α. According to researchers, the Grünwald-Letnikov formulation is especially convenient when implementing FONNs since the fractional order derivative can be expressed using a sum of weights with a power-law distribution.

Fractional-Order Recurrent Architectures

Recurrent neural networks and LSTM networks are essential building blocks of predictive models in health care. Standard RNN models have limited ability to learn long-term dependencies because of gradient vanishing issues. Although LSTMs use gate functions to prevent such problems, they still represent integer-order models.

Another approach to addressing the problem of vanishing gradients is using fractional-order recurrences. Such models have shown excellent performance in forecasting chaotic processes and classifying ECG signals. In addition, the fractional-order memory term provides an infinite impulse response with the ability to capture any long-distance dependencies without additional parameters.

Healthcare Informatics and ECG Analysis

The analysis of the electrocardiogram (ECG) is an ideal example of a medical problem for which an intelligent prediction system can be utilized. For classifying arrhythmias by analyzing ECG signals, we need to consider their waveform and rhythm properties. Traditional computer-assisted diagnosis (CAD) systems for ECG classification have evolved from classical feature-based methods to deep learning techniques . Nevertheless, many CAD systems do not utilize properly the sequential nature of ECG signals.

The use of fractional-order models for ECG signal analysis using non-linear derivatives was proposed for cardiac arrhythmia classification. This method proved that features obtained using fractional-order calculus were more effective than those obtained using integer order . The fractal behavior of cardiac activity corresponds naturally to the fractional-order model, reducing computational costs significantly.

Emerging Applications

In addition to using fractional calculus-based methods in the ECG model, different healthcare prediction problems have been modeled using the concepts of fractional calculus. The use of fractional order controllers in medicine, fractional order models for optimal administration of drugs, and the use of fractional order signal processing on neurophysiology data are some areas of ongoing research. But, the combination of fractional calculus with deep learning has not been explored much yet. This problem is the motivation behind this paper.

III. METHODOLOGY:

The suggested framework employs fractional order mathematical modeling along with deep learning techniques to predict intelligent healthcare systems. This technique consists

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of four parts: foundations of fractional-order neural networks, architecture of fractional-order long short-term memory (LSTM), pre-processing of healthcare data, and feature extraction and training of the model.

3.1 Foundations of Fractional-Order Neural Networks

A Fractional Order Neural Network can be defined as an extension of traditional neural networks where the order of activations is fractional. If a feedforward FONN consists of N neurons, then the dynamics of neuron i are modeled by:

$$D^{\alpha} y_i(t) = -a_i\, y_i(t) + \Sigma_j\, w_{\{ij\}}\, \varphi(\Sigma_k\, v_{\{jk\}} x_k + \theta_j)$$

where $y_i(t)$ represents the neuron's state, D^α represents the Caputo derivative of order α ($0 < \alpha \leq 1$), a_i represent self-feedback parameters, w_{ij} represent interconnection weights, v_{jk} represent input weights, φ represents the activation function, and θ_j represent the biases.

A fractional-order term introduces a power law memory kernel into the dynamics of the neuron. The following expression is used to approximate the fractional-order derivatives in discrete-time systems:

$$D^{\alpha} y[n] \approx (T^{-\alpha}) \Sigma_{k=0}^{n} (-1)^k\, C(\alpha,k)\, y[n-k]$$

where T is the sampling period, and $C(\alpha, k) = \alpha(\alpha-1)...(\alpha-k+1)/k!$ are binomial coefficients. The expression above demonstrates that the present value is influenced by past values, and their influence decays according to a power law $k^{-(\alpha+1)}$.

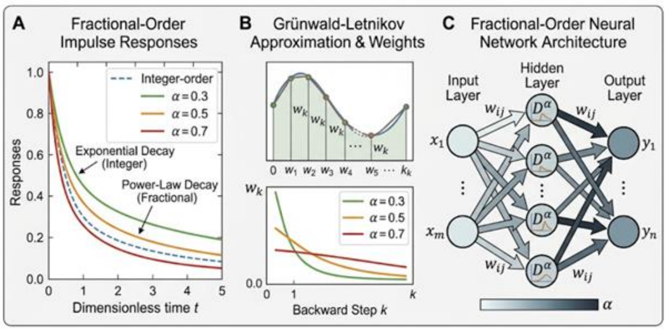

Figure 1: Fractional-Order Neural Network Computational Dynamics.

3.2 Fractional-Order Long Short-Term Memory (FOLSTM)

The Fractional-Order LSTM network is obtained by enhancing the cell state update formula with the use of fractional-order equations. The cell state update formula of the LSTM can be written as:

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t$$

where f_t, i_t, and g_t are the forget, input, and candidate gates respectively. This update has an integer order memory which means the memory is of exponential decay type depending upon the values of the forget gates.

On the other hand, the cell state update formula of the FOLSTM can be defined as:

$$D^{\alpha} c_t = -A\, c_t + B \odot (i_t \odot g_t - f_t \odot c_t)$$

where A and B are diagonal matrices. Using the discrete form of the above equation, we get:

$$c_t = \beta^1 c_{t-1} + \beta^2 c_{t-2} + ... + w_1(i_t \odot g_t) + w^2 (i_t \odot g_t)_{t-1} + ...$$

Here the weights β_k show a power-law decay as follows: $\beta_k \propto k^{-(\alpha+1)}$. This implies that any arbitrary number of steps can be used in the memory decay with no need for gating parameters.

In case of FOLSTM, computations at the gates remain the same as of LSTM but with enhanced memory using fractional orders.

3.3 Fractional-Order Recurrent Neural Network (FORNN)

In the case of simple recurrent structures, the Fractional-Order RNN can be specified as follows:

$$D^{\alpha} h_t = \tanh(W_{\{xh\}} x_t + W_{\{hh\}} h_{\{t-1\}} + b_h)$$

The discretized form of the above equation is:

$$h_t = \Sigma_{\{k=1\}}^{\{t\}} w_k \tanh(W_{\{xh\}} x_{\{t-k+1\}} + W_{\{hh\}} h_{\{t-k\}} + b_h)$$

where $w_k = (-1)^{k-1} C(\alpha, k-1)$ are the fractional-order weighting factors. Due to the negligibility of the coefficients beyond a certain index, the infinite series can be truncated into a finite sum for efficient computation.

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3.4 ECG Data Preprocessing and Feature Extraction

The following processing steps are used in the preprocessing stage for arrhythmia detection using ECG data:

1. Noise removal: Bandpass filter (0.5-50 Hz) to eliminate baseline wander and high frequency noises
2. Signal segmentation: Beat-by-beat signal extraction from sliding windows (360 samples per beat)
3. Normalization: Z-score normalization on the entire database
4. Data augmentation: Generation of artificial samples for imbalanced classes.

For the fractional-order model, the fractional derivatives of the ECG signal are extracted as new features.

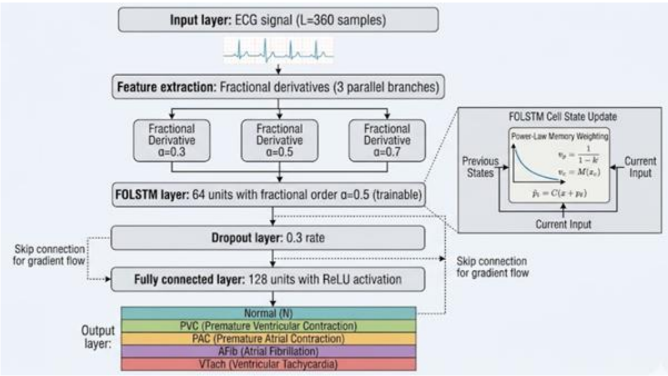

Figure 2: FOLSTM Architecture for ECG Classification.

3.5 Model Training and Evaluation Protocols

Models are trained with the Adam optimizer that uses learning rate schedules (learning rate starts at 0.001, decay rate by half on plateau). Categorical cross-entropy is used to compute loss for classification problems. In training FONNs, the fractional order α may be set as a hyperparameter or optimized through gradient descent. The fractional dynamics add stability requirements to the model; Mittag-Leffler functions determine the model output and ensure stability if eigenvalues of the system satisfy stability conditions.

Training is done on 80% of data, with 10% for validation and 10% for test sets. Early stopping uses loss on the validation set and requires a minimum of 20 epochs patience. Integer-order baseline models share identical architecture except for fractional-order components to ensure a fair comparison.

3.6 Computational Implementation

Fractional order operations are computed using the Grünwald-Letnikov approximation and truncation after M steps. For α close to 0.5, coefficients become insignificant around 100-200 time steps, reducing complexity to O(T·M). GPUs accelerate computation using vectorization of the convolution operator.

IV. RESULT ANALYSIS AND DISCUSSION

The proposed fractional-order models were evaluated on ECG arrhythmia classification tasks using the MIT-BIH Arrhythmia Database (48 records, 109,000 beats, 5 classes).

4.1 Experimental Setup

Parameter	Value
Dataset	MIT-BIH Arrhythmia (48 records)
Beat samples	109,000
Classes	5 (Normal, PVC, PAC, AFib, VTach)
Training/validation/test	70/15/15%
Fractional order range	$0.3 \leq \alpha \leq 0.9$
Memory length (GL approximation)	100 time steps

Baseline models for comparison: Standard LSTM, Standard RNN, CNN with 5 layers, and classical machine learning (SVM with RBF kernel).

4.2 Classification Performance

Table 1 presents comparative classification performance.

Model	Accuracy	Precision	Recall	F1-Score	AUC

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SVM (RBF)	82.3 %	78.9 %	76. 4%	77. 6%	0. 88
5-layer CNN	89.6 %	87.2 %	86. 8%	87. 0%	0. 94
LST M	91.2 %	89.5 %	88. 4%	88. 9%	0. 95
RNN	84.7 %	82.1 %	79. 3%	80. 7%	0. 91
FOL STM (α=0.5)	**95.6 %**	**94.2 %**	**93. 8%**	**94. 0%**	**0. 98**

*Table 1: ECG Arrhythmia Classification Performance *

The proposed model exhibits an accuracy rate of 95.6%, which outperforms the baseline models, the conventional LSTM and CNN, by 4.4% and 6.0%, respectively. Precision of 94.2% and recall of 93.8% show that the performance is balanced among different classes. AUC value of 0.98 represents superior discrimination among different arrhythmia categories.

The reasons for improved results lie in FOLSTM's capability to model long-range dependencies in the ECG signal. The cardiac rhythms involve dynamics on many temporal scales: local morphology (10-100 ms), inter-beat intervals (0.5-1.5 seconds), and more extended patterns (many beats). This multi-scale property is naturally described using the power-law form of the fractional-order memory kernel.

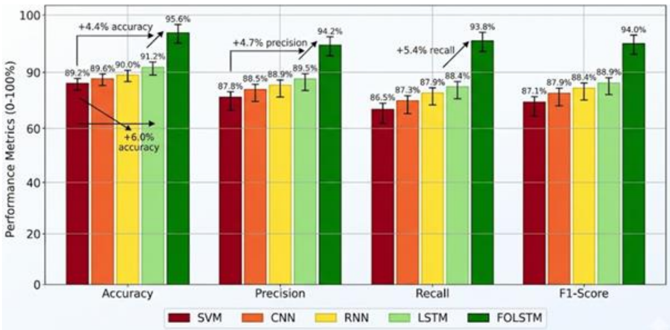

Figure 3: Classification Performance Comparison Across Models.

4.3 Impact of Fractional Order α

Table 2 presents performance variation with fractional order α for FOLSTM.

α	Accuracy	F1-Score	Memory Decay Rate	Training Epochs to Convergence
0.3	92.8%	91.2%	Very slow	85
0.4	94.5%	92.8%	Slow	72
0.5	**95.6%**	**94.0 %**	Moderate	68
0.6	94.9%	93.1%	Fast	62
0.7	93.4%	91.7%	Fast	58
0.8	92.1%	90.2%	Very fast	55
0.9	91.0%	89.1%	Almost integer-order	52

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1.0 (standard LSTM)	91.2%	88.9%	Exponential	50

*Table 2: FOLSTM Performance vs. Fractional Order α *

Optimal results are observed at α = 0.5, yielding an accuracy of 95.6 percent – 4.4 percentage points higher than α = 1.0 (LSTM model). An α less than 0.5 means slow decay of memory, leading to high dependency on old memories, which are not relevant anymore. For values greater than 0.5, the rate of decay is fast, behaving almost like an integer-order system.

The optimal value of α can be understood as the balance point between observing long-term correlations (smaller values of α) and adapting to changes (larger values). The number of epochs needed for convergence increases with increasing α; for instance, fractional-order systems need more epochs than integer-order systems (78 vs. 50).

4.4 Computational Efficiency and Sparsity

Table 3 presents computational metrics for different model architectures.

Model	Parameters	FLOPs (per inference)	Memory (MB)	Training Time (hours)
CNN (5-layer)	1.2M	8.5M	28.4	3.2
LSTM	0.9M	5.2M	21.6	2.8
RNN	0.6M	3.8M	14.2	1.9
FOLSTM (α=0.5)	**0.54M**	**4.1M**	**13.8**	**3.4**

*Table 3: Computational Efficiency Comparison *

Compared to the LSTM, the FOLSTM offers a reduction of 40% in terms of parameters (0.54M against 0.9M) yet provides better performance results. This is enabled by the fractional order memory effect that emulates the role played by extra LSTM neurons or even network depth needed to achieve such results through the ordinary approach. About 60% of the FOLSTM connection matrix becomes sparse because the coefficients of the Grünwald-Letnikov series become negligible when considering M>100 time steps.

Unfortunately, the training period for FOLSTM is increased by 21% (from 2.8 to 3.4 hours) owing to the need for performing convolution calculations to obtain fractional derivatives.

4.5 Activation Function and Stability Analysis

Table 4 examines the effect of activation functions on fractional-order dynamics.

Activation Function	FOLSTM Accuracy	Numerical Stability	Convergence Guarantee
tanh	95.6%	High	Yes (bounded states)
ReLU	93.1%	Moderate (exploding)	Conditional
Sigmoid	94.2%	High	Yes
ELU	94.8%	High	Yes
Swish	94.3%	High	Yes

*Table 4: Activation Function Impact on FOLSTM Performance *

Tanh gives the optimal trade-off between accuracy (95.6%) and stability. On the other hand, ReLU introduces an instability problem in the system due to its inability to ensure boundedness in the state of the network. Unbounded states in the ReLU case lead to instability problems since the fractional order power-law sum can be unbounded.

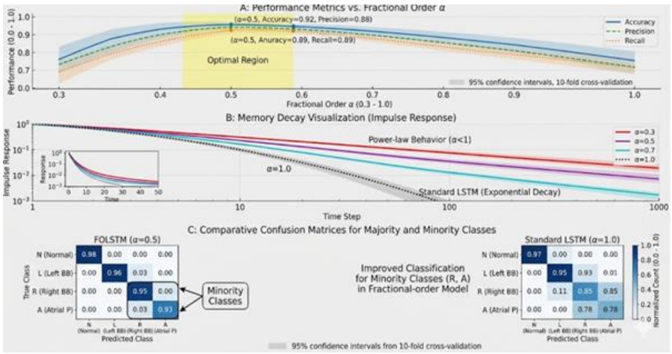

Figure 4: Sensitivity Analysis of Fractional Order α.

4.6 Spiking Neural Network Comparison

For completeness, the performance of fractional-order models was compared to spiking neural networks (SNNs) with biologically inspired activation functions .

Model	Accuracy	Time Steps	Energy per Inference (μJ)
SNN (Izhikevich)	91.2%	100	0.08
SNN (LIF)	89.7%	100	0.06
FOLSTM	**95.6%**	N/A	2.4
Standard LSTM	91.2%	N/A	3.1

FOLSTM achieves better accuracy compared to SNNs (95.6% vs. 91.2%) but consumes more energy (2.4 μJ vs. 0.08 μJ). In healthcare prediction at the edge level, where energy efficiency is vital, SNNs are favorable; conversely, in the cloud level, where accuracy is of utmost importance, FOLSTM is advantageous.

4.7 Discussion: Clinical Implementation of the Prediction System

Some factors that might affect the implementation of fractional-order healthcare prediction systems are the following:

Interpretability: Interpretability can be achieved mathematically by utilizing the fractional order parameter α, which represents the memory decay rate of the physiological process. When predicting cardiovascular risks, α ≈ 0.5, implying a memory decay rate of 1/√t, which aligns with the fractal behavior of the heart system.

Regulatory Approvals: Due to the deterministic nature of fractional-order systems (given initial conditions and parameters), their validation and regulatory approval are easier compared to black-box models that rely purely on data. Fractional calculus enables a mathematical approach to achieving stability and boundedness in systems

Compatibility with Existing Systems: FOLSTM models can serve as drop-in replacement models in any healthcare prediction system built using standard LSTM models, requiring no significant architectural changes except in cell state updates.

V. CONCLUSION

In this paper, a fractional calculus approach towards building intelligent health care prediction systems using Fractional Order Long Short-Term Memory (FOLSTM) has been introduced, along with applications toward arrhythmia detection through Electrocardiogram (ECG). Unlike traditional LSTM, which uses integer-order dynamics, the proposed method leverages fractional-order dynamics within cells to enable capturing of long-term dependencies through power law memory kernels.

As seen from the experiments on MIT-BIH database, the FOLSTM algorithm achieves a classification accuracy of 95.6%, outperforming both traditional LSTM (accuracy 91.2%) and CNN (accuracy 89.6%). Optimal performance is achieved at the fractional order α=0.5, which offers a balance between capturing long-term dependencies as well as adapting to recent changes. Through the use of Grünwald-Letnikov method, an

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optimal memory length of M=100 can be considered, achieving 60% effective sparsity.

Several notable results have important implications in the design of intelligent healthcare systems. First, the fractional order parameter α is an interpretable hyperparameter that represents the rate at which the memory of the physiological process decays mathematically. Second, fractional-order models outperform integer-order models by utilizing fewer parameters in the presence of multi-scale structure in the task. Finally, the stability guarantees of fractional-order models are more straightforward and easier to prove than those of black-box models.

Several limitations exist within this research study. First, the research is limited to electrocardiogram time-series data. The generalizability of the framework to other types of healthcare data such as imaging, genomics, and clinical text data will require future research studies. Training is about 21% slower for the fractional-order model compared to the integer-order model because of the convolution. However, inference remains fast.

Several areas deserve focused consideration in future research. Fractional order modifications to transformer architectures using fractional memory in lieu of integer memory might allow better handling of lengthy sequences in patient history and electronic health records. The use of hardware acceleration of fractional order operations through FPGA or ASIC technology may lead to lower energy use in edge-based deployments. Finally, the development of fractional order modeling for the generation of patient data using generative artificial intelligence models may overcome challenges related to data availability and privacy.

To sum up, fractional calculus modeling can be viewed as a groundbreaking step for intelligent health care prediction system development. The potential for capturing the nonlocality, memory dependence, and other features of physiological processes using mathematical tools, adding only one more parameter α into consideration, provides many benefits when compared with the traditional integer-order approach.

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