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Original scientific paper

Dual Optimized Event Prediction Using Meta-Heuristic Algorithms with a Distributed Deep Model for Multi-Event Forecasting

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Abstract: In today's technology-driven decision-making era, there is a growing demand for methodical solutions that leverage hybrid nature-inspired protocols with deep learning models (DLM). An evolution in data management through structured systems is essential. We propose a revolutionary method that combines two algorithms with distributed learning to address vast and high-velocity data streams, tackling challenges associated with noisy and imbalanced raw data sources. This study introduces an innovative integration of two nature-inspired protocols for feature selection, specifically targeting multi-event and unbalanced medical data sources in time-series-based event prediction models for source optimization. Our work utilizes the Dragonfly and Tuna Swarm algorithms within a hybrid optimization framework for feature selection. Additionally, we designed a Distributed Deep Model (DDM) to achieve high classification and prediction accuracy for multi-event data sources. Our proposed Dual Optimized Event Prediction with Distributed Deep Model (Dual-OEP-DDM) excels across key performance metrics, including accuracy, precision, recall, and F1-score. Comprehensive evaluation in dynamic event environments demonstrates that our model achieves an accuracy of 99.94%, sensitivity of 99.86%, F1-score of 99.87% (in single-event scenarios), and specificity of 99.89%, showcasing its superiority over existing models.

Keywords: data classification; distributed deep learning; hybrid optimization; nature-inspired algorithms; multi-event prediction

1 INTRODUCTION

Currently, advancements in medical and science technology have resulted in the creation of extensive medical data sources that encompass multiple elements [1], including terminated and useless features. Information source dependent based decision-making in high-risk diseases, such as cardiovascular conditions [2], is a prominent trend wherein numerous data mining and machine learning techniques are implemented. Medical data are sourced from various origins, resulting in the inclusion of unnecessary and irrelevant information that may impair the efficiency of algorithms in information based decision-making tools [3]. Irrelevant and redundant data can be eliminated as they do not enhance classification accuracy; irrelevant data exhibit moderate connection with the class, whereas redundant data demonstrate substantial association with one or more features [4].

Metaheuristic optimization algorithms are primarily derived from natural phenomena. The ease of construction and adequate outcomes of swarm intelligence (Sw-In) algorithms for diverse challenges have rendered several of them highly appealing and widely adopted. Due to the NP-completeness of feature selection [5-8], Sw-In algorithms are extensively employed to address this issue. Nonetheless, the majority of binary SI algorithms lack the efficacy and scalability required to choose optimal features from vast and unbalanced datasets.For that reason, in our work we proposed the merging of two nature inspired protocols for selecting the optimal features of the dynamic different data sources. From the optimized different time event features our focus is to classify and efficently predict the multievent optimized outcome; for that reason we designed and proposed the distributive deep model.

2 RELATED WORKS

Numerous distinct discrete issues, including Selection of feature planning the tour, complicated systems, and the traveling salesman problem, necessitate resolution through discrete optimization techniques. Obligatory-based approaches commonly utilize discrete metaheuristic optimization algorithms as search strategies to address feature selection issues and identify effective subsets of feature [9-13]. A different approach is to make use of the transfer function, also known as Trs-F. This function transforms the continuous search space into a binary manner, allowing search node to go to corners of a convergence spaces that are closer or further away by flipping a number of states [14-17]. Therefore, transfer functions make use of a mapping function in order to determine the likelihood of a solution moving in the middle of zero to one value.

In recent years, the protocol of recurrent neural networks (Rc-NNs) has demonstrated superior efficacy in sequence modeling, such as natural language modeling [18-20]. Standard Rc-NNs experience issues with together vanishing and exploding gradients. Long Short-Term Memory mitigates the vanishing gradient problem by the parameterization of recurrent neural networks. Such prediction models failed to account for the relationships between events and their qualities, focusing instead on identifying the intrinsic variations within event sequences.

Connotation rule mining algorithms have demonstrated efficacy in various areas, including web log analysis. In [21-24], the author introduced a program for analyzing a novel bug report and generating order based options. This tool determines the configurability of the report. Nevertheless, there is a drawback to the order rank identification step when dealing with configurations order value that contain different words. The tool tends to select the configuration with longer words, even though the one with shorter words is actually the correct one.

In summary, these mentioned conventional models and methods fluctuate their performance for multi-event unbalanced data sources [25-28]. To overcome these limitations, we proposed the efficient reliable model of Dual-OEP-DDM for multi-event optimized prediction.

3 PROPOSED SYSTEM

The proposed Dual-OEP-DDM model integrates with the hybrid meta-heuristics to distributive deep model

(DDM). We used two nature-inspired algorithms, namely the Dragonfly Algorithm and the Tuna Swarm Optimization Algorithm; these two protocols are hybridized to achieve the optimal solution for different medical database events. After the optimization of the features, the feature set $\{E_0, E_1, \ldots, E_n\}$ is fed to input of the proposed DD-model.The feature selection process plays a critical role in this study, as the Dual Optimized Event Prediction model (Dual-OEP) seeks to optimize classification by reducing data dimensionality and selecting the most predictive features. Using the Dragonfly and Tuna Swarm Optimization (TSO) algorithms, features are ranked based on their relevance to the outcome variable in a multi-event prediction task. These algorithms mitigate issues like local minima, ensuring optimal feature selection that directly improves the model's efficiency and accuracy. By focusing only on the most impactful features, the model minimizes computational requirements and enhances interpretability, ultimately leading to improved performance metrics such as higher accuracy, precision, recall, and F1-score, as observed in the results.The Fig. 1 shows our proposed Dual-OEP-DDM system.

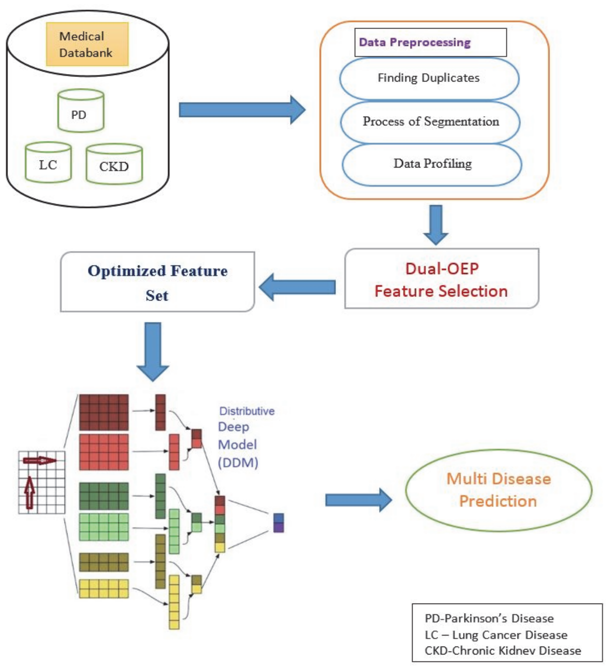

Figure 1 Proposed Dual-OEP-DDM system

Proposed Hybrid Architecture for Feature Selection

The hybrid design starts with the dragonfly algorithm followed by the tuna swarm optimization protocol.The hybrid system of feature selection is described as follows,

$$S_s = -\sum_{neigh=1}^{M} (X_{indi} - X_{neigh}) \tag{1}$$

In Eq. (1), the variable S_s represents the separation of individuals, the location of each individual in the population is X_{indi} and the nearby agent within the population is X_{neigh}. Depending on the population, each medical event dataset is distributed after the data preprocessing stage.

$$A_a = \sum_{k=1}^{M} R_k \tag{2}$$

In Eq. (2), the variable A_a represents the alignment of two agents' velocities, the variable R_k denotes the rate of individual agent velocity, with the reference of the rank the event dataset attributes are assigned the local fitness values.

$$C_C = \frac{\left(\sum_{neigh=1}^{M}\left(X_{neigh}\right)\right)}{M} - X_{indi} \tag{3}$$

In Eq. (3), the variable C_C represents the individual consistency, this value is used to measure the flying procedure of the center to each other. In this stage the primary event data value features are focused towards the global point source parameter of the event dataset.

$$F_{indi} = X^{fl} - X_{indi} \tag{4}$$

$$E_{indi} = X^{el} + X_{indi} \tag{5}$$

In Eqs. (4) and (5), the variables F_{indi} and E_{indi} represent the food attraction and enemy distraction values based on the current location of individuals; this value is used to measure the fitness value of each individual. With this reference the primary final fitness of the event dataset features $X^{t}_{df(best)}$ are assigned to the second level of optimization using tuna swarm protocol.

In Eq. (6), the variable $X^{t=1}_{i(tu)}$ defines the current value of the tuna swarm optimization population node; the notations α_{11} and α_{22} are used to weights of the coefficients, assigned to guide individual movements as well as to steer towards the optimal fitness of the features. Using Eq. (7), the final optimal feature fitness of the event database attributes is assigned with reference to the tuna swarms at each iteration.The complete hybrid design is detailed in Algorithm 1.

Proposed DDM for Optimal Prediction

The primary focus of the proposed method is to achieve parallelism across different event (medical dataset) features, thereby increasing the overall feature throughput rate of the proposed predictive model, the Distributive Deep Network Model (DDM).

Algorithm 1 optimizing the dataset features using Hybrid meta-heuristic protocol

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1. Input : a medical dataset with clinical attributes; proposed D-OEP algorithm parameters - population size M, the random agent X, R_k , α_{11} and α_{22}
2. Result: The optimized feature parameter of the given dataset $\{E_0, E_1, \ldots, E_n\}$
3. Initialization:

$(D-OEP) \leftarrow \{M, \alpha_{11}, \alpha_{22}, X_{indi}, \beta_{df}, \eta\}$

for i = 0, 1, 2….. $\max_{iteration}$
Measure individual fitness using Eq. (1)
Calculate the data features rank using the Eq. (2)
Finding the global optimal features using the Eqs. (3) and (4)
Feed the primary optimal values to second population local fitness using Eq. (6)
Verify the final optimal feature score using the Eq. (7)
Update the model

$\eta \leftarrow$ current fitness value

End for

4. Output: Getting the best final optimal solution of medical event attribute feature E_n

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The DDM methodology provides a detailed description of faster loss functions. An additional specialty of this method is that it performs backpropagation in parallel mode. In DDM, the feature samples of a particular event database are not interpreted together with the cumulative individual parameter gradients of other event features. The gradient function is calculated using the subsets $\{E_0, E_1, \ldots, E_n\}$ of the mini-batch (E). The cumulative individual parameter gradients for the complete input feature sample batch are given as:

$$\frac{\partial Y(z;\omega)}{\partial \omega} = \frac{\partial Y(z_1;\omega)}{\partial \omega} + \ldots + \frac{\partial Y(z_n;\omega)}{\partial \omega} \tag{8}$$

Therefore, the 64-sample mini-batch is divided into clusters within a double feature set. Afterward, each feature set processes 32 samples in parallel mode, without cross-validation. This process demonstrates that our proposed predictive model (DDM) requires only half the number of training samples and also reduces the computational complexity of the model.

The complete pseudo-code of the DDM model is detailed in Algorithm 2.

Algorithm 2 proposed distributive deep model (DDM)

Required: Initial model state ω_0 , number of feature sets $\{E_n\}$

$t \leftarrow 0$

Main Loop

1. Establish the current state ω_t
2. Model processing $\omega_{t+\tau}^{i}$ for all features

   $\tilde{\omega}_i \leftarrow$ sum average of $\omega_{t+\tau}^{i}$

   $t \leftarrow t+\tau$
3. For $u \leftarrow t+1, t+2, \ldots t+\tau do$
4. Sample min-batch using Eq. (8)
5. End for loop
6. End main loop
7. Result: update the feature set order for optimal event prediction

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$\tilde{\omega}_i$ --→ Current network layer

$\omega_{t+\tau}^{i}$ -→ Next event time prediction layer node parameter

u --→ expected total number of feature layers

4 RESULTS AND DISCUSSION

For this research work, the datasets used for training and testing the model consist of multi-event data sources with imbalanced distributions, particularly in the medical domain, as they present complex challenges in data prediction and classification. These datasets include various clinical event records and patient health data captured over time, reflecting unbalanced characteristics due to the differing frequencies of certain medical events. The datasets are sourced from publicly available medical event prediction repositories, and they include features such as patient demographics, medical history, event timestamps, and diagnostic labels. This data is divided into training and testing sets, typically following a split of 80% for training and 20% for testing. This division ensures sufficient data for model generalization while maintaining a robust test sample for accuracy assessment.

The experimental findings derived from the Dual-OEP-DDM model and several customary models key performances are investigated. The efficacy of the proposed Dual-OEP-DDM and alternative methodologies is evaluated using various input feature sets. The models are first trained with all available features, after which the proposed Dual-OEP-DDM is utilized to discern pertinent features. In result, the methods of the classifiers are provided with the features that were selected with great care as their input. A number of different performance measures are utilized in order to evaluate the outcomes of each model.

To enhance reproducibility, the following parameters were used for the Dragonfly and Tuna Swarm Optimization algorithms:
Population size: 30
Number of iterations: 100
Spiral updating mechanism: enabled for improved convergence
Exploration-exploitation balance: dynamically adjusted
Convergence threshold: 0.0001

The results of the Parkinson's disease data sets, chronic kidney disease, and chronic obstructive pulmonary disease are presented in Tab. 1 to Tab. 3.

Table 1 KPI metrics comparison for Chr-KD prediction

Methods	$Acc_{\%}$	$Pre_{\%}$	$Rec_{\%}$	$F1_{\%}$
Proposed D-OEP-DDM	99.94	99.96	99.98	99.97
CSSA-DLEDC	99.60	99.30	99.20	99.24
KDSAE	99.40	99.01	99.10	99.02
Ensemble ML	99.31	99.24	99.46	99.31
DNN	99.68	99.72	99.63	99.70

The proposed model as well as the conventional model accuracy of the individual event (Individual medical dataset) are compared in Fig. 2 and Fig. 3. In Tab. 1 to Tab. 3 we have shown the event predictions models efficiency in terms of the following fruition's metrics, the accuracy - $Acc_{\%}$, the precision - $Pre_{\%}$, Recall - $Rec_{\%}$ and finally F1-Score as $F1_{\%}$.

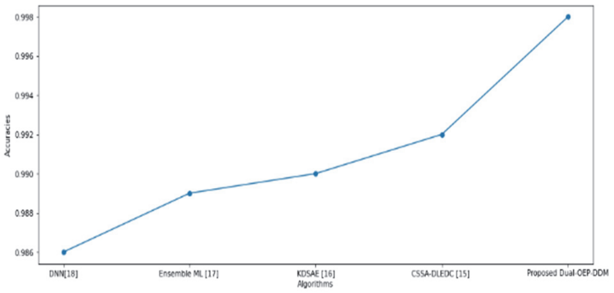

Figure 2 KPI metrics assessment for Chr-KD dataset

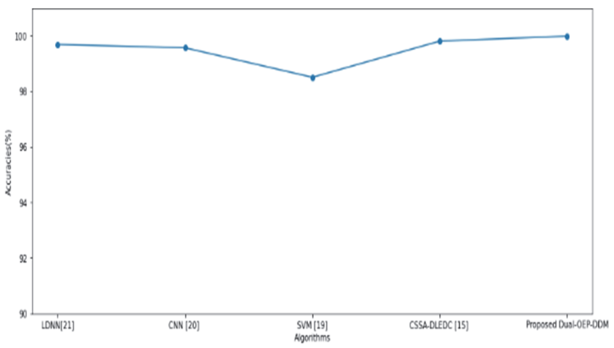

Figure 3 I KPI of Proposed Dual-OEP-DDM Model for Multi-Event datasets

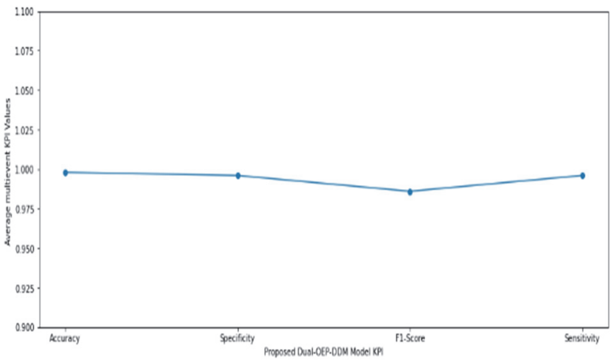

Figure 4 KPI of Proposed Dual-OEP-DDM Model for Multi-Event datasets

Table 2 KPI metrics comparison for Lung-C prediction

Methods	$Acc_{\%}$	$Pre_{\%}$	$Rec_{\%}$	$F1_{\%}$
Proposed D-OEP-DDM	99.99	99.98	99.96	99.97
CSSA-DLEDC	99.80	99.50	99.40	99.50
SVM	94.98	92.54	95.56	99.51
CNN	99.56	93.40	94.60	92.40
DNN	99.78	99.49	99.39	99.48

Table 3 KPI metrics comparison for Par-D prediction

Methods	$Acc_{\%}$	$Pre_{\%}$	$Rec_{\%}$	$F1_{\%}$
Proposed D-OEP-DDM	99.98	99.90	99.98	99.95
CSSA-DLEDC	99.94	99.49	99.52	99.51
ANN+SVM	99.30	98.44	98.20	98.35
CNN +RFC	99.28	99.10	99.24	99.18
MLP+GBD	99.15	98.98	98.76	98.99

Table 4 Proposed models complete event evaluation Metrics

Model	*Accu*	Specificity	F1 Score	Sensitivity
Dual-OEP-DDM	0.998	0.996	0.986	0.996

With the evidence of the Key recital factor vales from Tabs. 1 to 3, the proposed Dual-OEP-DDM model's comprehensive multi-event predictive performance of different medical datasets issummarized as Tab. 4 and Fig. 4.

Compared to existing prediction models, the Dual-OEP-DDM stands out for its combination of nature-inspired optimization and deep learning, which enables superior feature selection and classification accuracy. Standard machine learning approaches like SVM or random forests typically struggle with unbalanced datasets and often require extensive preprocessing to mitigate this issue. In contrast, Dual-OEP-DDM's integration of Dragonfly and Tuna Swarm algorithms enhances feature selection specifically in imbalanced data contexts, resulting in improved accuracy (99.94%), F1-score (99.87%), and sensitivity (99.86%). Additionally, deep learning models like CNNs and LSTMs may achieve high performance in time-series predictions but often lack the interpretability and optimization that meta-heuristic algorithms provide. Overall, our model's hybrid nature offers a more robust solution by effectively combining feature selection and predictive accuracy.

5 CONCLUSION

This paper proposes a Dual Nature-Based Protocol (Dual-OEP) that effectively performs feature selection on unbalanced multi-event datasets. By integrating Dragonfly and Tuna Swarm algorithms, our approach overcomes the challenge of local minima in feature selection, leading to an optimized feature set for classification. The proposed Distributed Deep Model (DDM) processes and organizes data in an optimized order, leveraging hidden layer interactions to enhance multi-event classification and prediction accuracy. Experimental results indicate that our Dual-OEP-DDM model achieves outstanding performance, with an accuracy of 99.9%, sensitivity of 99.6%, and F1-score of 98.67% in single-event scenarios, along with a specificity of 99.60%, demonstrating its robustness in dynamic environments.For future enhancements, we aim to explore the integration of additional meta-heuristic algorithms to further refine feature selection and optimize computational efficiency. Additionally, extending the model to adapt to real-time data streams and handle increasingly complex multi-event environments will be prioritized. We also plan to investigate the model's scalability and effectiveness across a wider variety of domains, including finance, environmental monitoring, and social media data, to broaden its applicability and impact.

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