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# ECG Signal Processing using an Optimized Sliding Window Approach for Concept Drift Detection and Adaption

**Ketan Sanjay Desale[*] and Swati V Shinde**

*Department of Computer Engineering, PCCOE, Pune, India*

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***Abstract***

Due to dynamic smart systems, concept drift in live streaming data is a typical issue, resulting in performance reduction. Despite the fact that there are a variety of traditional ways of handling streaming data, they still need to address notion drift, necessitating the development of an adaptive approach to managing dynamic streaming data. As a result, a new strategy for dealing with idea drift difficulties in online data streaming is experimented with in this study. This study creates a dynamic streaming data analysis system based on an optimized Deep CNN and an optimized adaptive and sliding window (OASW) technique that efficiently tackles memory and time restrictions. For offline learning, an optimized Deep CNN classifier is used as a base classifier, which is created by combining Desale's aggressive hunt optimization (AHO) method with the Deep CNN classifier to tune the classifier's ideal parameters. This study uses an optimized adaptable and sliding window to adjust pattern changes in data streams, successfully handling concept drift. The proposed methods exceed the traditional methods in terms of specificity, sensitivity, accuracy, F1 score, and precision score of 94.55%, 95.78%, 95.98%, 96.47%, and 96.87%, respectively, according to the experimental study.

*Keywords:* data stream, concept drift, deep learning, optimization.

## 1. Introduction

Due to the contribution of the smart gadget, which has now become an indispensable component of human day-to-day life [5], there has been a rapid increase in technical innovation in the previous few decades. Due to the effect of data distribution of the gathered observation, there may be some reflection in the concepts in the data streams. The areas that rely on security, monitoring, and control necessitate precise and quick distribution change detection-[14][15]. Some examples of monitoring and control systems are the mobile tracking system, which tracks user activity, and the intrusion detection system, which monitors anomalous actions [16][17]. In prior literature [13], differences in the distribution of data streams are referred to as concept drift. Real data is not immediately used for detection and classification systems because the concept drift process decreases detection and classification accuracy [12].

The hidden and unknown relationship between the input and output variables is described by the term "concept drift" [11]. The idea of drift is divided into two types based on the rate of variation: gradual and rapid drifts. The considerable variation between the distribution class and the received samples in a specific time period is termed an abrupt or quick gradual drift. The variation category is tallied, and it must be meaningful in order to correctly display and find the variances [9]. Concept drift is categorized into several forms based on its period or rate of change, such as incremental, sudden, gradual, and recurring. These classifications are depicted in Figure 1. During the idea transformation process, research into concept drift adaptation in Types A to C focuses on minimizi ng the loss of accuracy and obtaining the quickest recovery rate possible.

On the other hand, Type D drift research focuses on applying historical notions, especially how to find the best match archive concepts in the shortest time possible. The following notion might arise right once, gradually, or over time. Because more data is piled together to produce data streams rather than organized in static databases, idea drift difficulties are more effective for data mining and machine learning [10].

A new drift adaptable framework for online streaming data analytics is provided in this study. The suggested framework includes an offline learning Deep CNN network optimized using Desale's Aggressive hunting optimization (AHO) [27]. Furthermore, during the incremental learning step, the proposed model employs an optimal adaptive and sliding window (OASW) for idea drift adaption. The suggested drift detection and adaptation mechanism is tested using the reference dataset, the MIT-BIH ECG dataset.

- **Desale's Aggressive Hunting Optimization:** Aggressive hunting optimization is a nature-inspired algorithm that was created by combining the sea lion and coyote's hunting characteristics.
- **AHO-based Deep CNN:** The Deep-CNN classifier is used to identify and adapt to idea drift, with the hyper-parameters of the classifiers being optimally adjusted by the proposed Aggressive hunting optimization.

Any drift may be discovered, and if the drift does not occur before, the deep CNN updates the knowledge about the drift and continues, which aids in efficiently identifying the idea of drift. As a result, this study can adopt new patterns even in the presence of noise, and the suggested model might perform well where the memory is also

*E-mail address: desaleketan.10@gmail.com
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optimized using the research's proposed optimization, which tends to tackle the above issues.

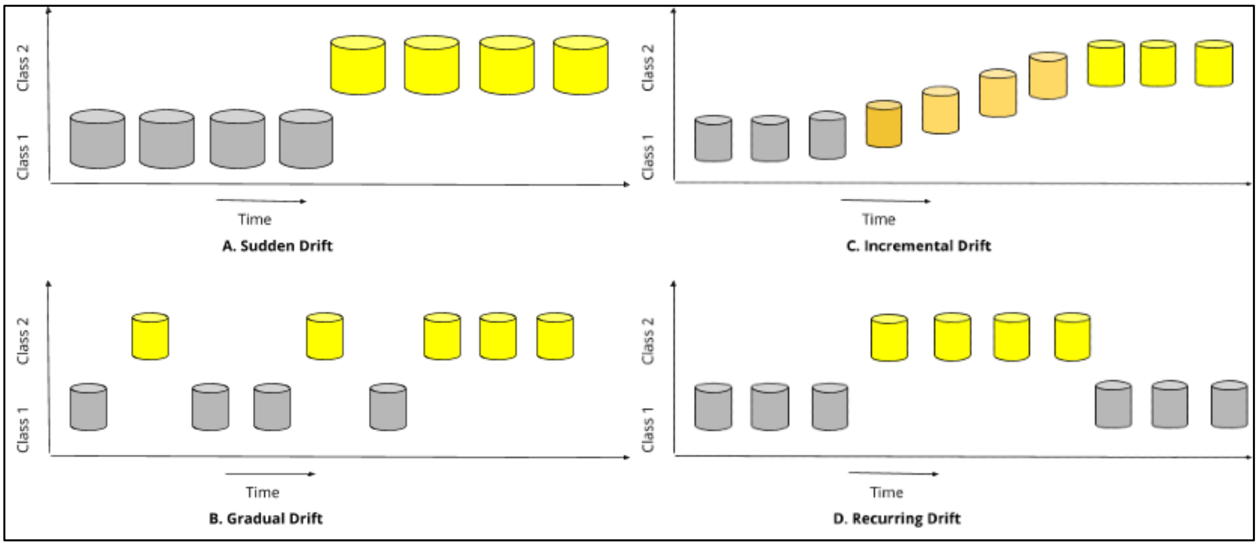


**Fig. 1**. Concept Drift Types: A. Sudden Drift B. Gradual Drift C. Incremental Drift D. Recurring Drift

The remaining text in the paper is organized as follows: section 2 contains a review of the literature as well as the necessity for the concept drift detection model. In section 3, the proposed idea of the drift detection and adaptation model is explained, and the result analysis is discussed in section 4. Finally, in section 5, the paper's conclusion is shown.

## 2. Literature survey

The advanced concept drift prediction, the adaptive method's needs, and the significant obstacles connected with traditional approaches are outlined below.

With respect to frequency and updating time, Abdulbasit A. Darem et al.[1] proposed sequential deep learning and achieved improved efficiency and accuracy. The sequential deep learning model, on the other hand, lacked tagged examples. Lukasz Korycki et al. [2] developed the Robust Restricted Boltzmann Machine for Drift Detection, which has a high detection rate and is resistant to adversarial attacks. Fuzzy Distance Estimations were utilized by Anjin Liu et al. [3], and the findings were more trustworthy. High-dimensional data sets resulted in a significant rise in computation costs. To reach the optimum security level, Rongbin Xu et al. [4] employed time-series issues. Furthermore, the findings were supported by static data. Concept-Drift-Aware Federated Averaging (CDA-FedAvg) adaptive adjustments in non-stationary settings were introduced by Fernando E. Casado et al. [5]. This strategy did not explore the spatial dimension. Multivariate Hoeffding's bound technique was utilized by Pravin Nagar et al. [6]. This approach does not over-segment and properly locates the temporal limits. However, the issues where movies were taken at extremely low temporal resolution were not resolved. Jaka Demsar et al. [7] proposed a technique for finding concept drifts that effectively dealt with redundancy, disjunctions, and noise. The high degree of parameterization and necessary calculation time were the key drawbacks. Adaptive deep neural networks were used by Husheng Guo et al. [8]. The model's ability to match data distributions has increased, but it still can't handle high-dimensional nonlinear situations.

Priya.S and Annie Uthra.R [10] used the Statistical Test of Equal Proportions - Kernel Extreme Learning Machine (STEPD-KELM) model to develop an effective solution for identifying email spam. The accuracy value, on the other hand, has declined throughout the recent window sample. The Adadelta optimizer-based deep neural networks (ADODNN) model was described by Yifei Yuan, Zhixiong Wang, and Wei Wang [11] as an efficient solution for classifying highly unbalanced streaming data. However, feature selection and clustering techniques were not employed in this strategy to reduce computing complexity.

Processing and storing streaming data presents significant challenges, and data analytics speed must be faster than data collection/generation time. Many causative causes and various types of drifts in streaming data are two major issues in drift identification. Adapting to changing data patterns and successfully managing observed drift following drift detection is a tough undertaking. While shielding many forms of data from noise, such as embeddings, extracted features, and created instances.

## 3. Proposed methodology for handling the concept drift:

The primary goal of this study is to create a dynamic streaming analytics system that addresses the challenges of online streaming data for concept drift. The proposed concept drift model included two phases for drift detection: offline learning and incremental learning. Figure 2 depicts a diagrammatic depiction of the proposed improved Deep CNN. Incremental learning is used to determine the attacks/variants in the online data streams, while the offline learning is used to obtain the initial training model. The real-time stream data is obtained in the offline learning phase to produce the historical dataset, which is utilized to train the Deep-CNN model. The proposed AHO algorithm, a meta-heuristic approach for developing the optimal Deep-CNN model, successfully tunes the hyperparameters of the Deep-CNN model.

The continually created data streams are analyzed in the incremental learning phase to discover concept drifts in the online streaming data. The trained base classifier is used to process the data streams at the beginning. If the concept drift is identified using the suggested AHO algorithm-based deep

CNN classifier as the basis classifier, the classifier is retrained using fresh sample data gathered by the AHO method to be suitable for the present idea drifts. As a result, the suggested concept drift prediction model adapts to changing streaming data samples, resulting in the most accurate detection.

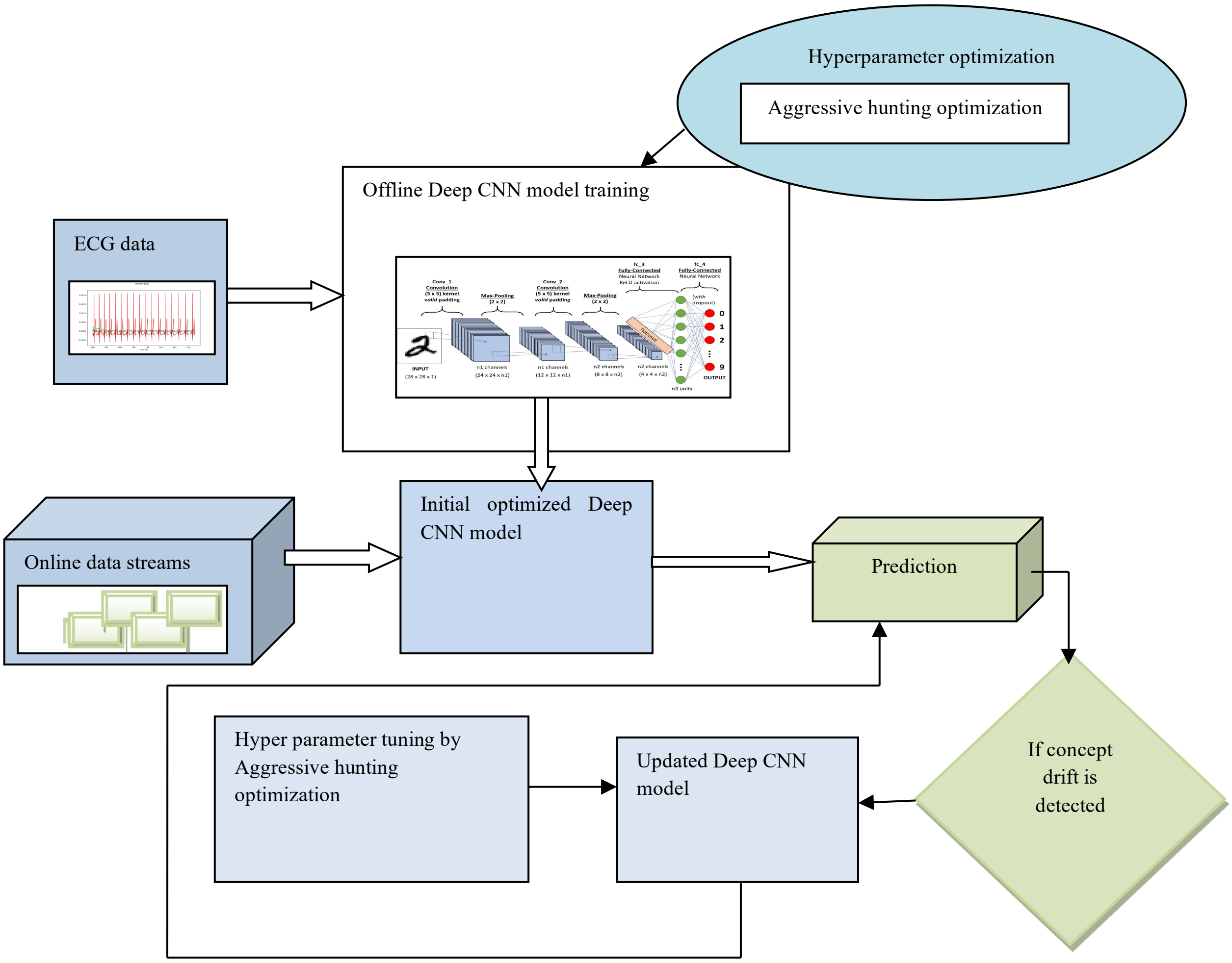


**Fig. 2.** Diagrammatic representation of the Adaption Framework using Optimized Deep learning for detection

The Desale's AHO algorithm is a meta-heuristic algorithm in which a new search agent is created by combining the influential hunting qualities of the Sealion and the Coyote's dominance rule. Optimizers are programs or procedures that adjust the neural network's weights and learning rates in order to minimize losses. The optimisationOptimization is used in deep learning to optimize the classifier's hyperparameters.

**4. Result and discussion**:

This section outlines the outcomes of the concept drift detection and adaption approach.

**4.1 Experimental setup**: The proposed concept drift determination and the adaptation model are implemented in the Python Windows 10 operating system, 8 GB RAM, and ROM with more than 100 GB. MIT-BIH Arrhythmia Dataset is used for experimentation.

**4.2 Dataset Description**:
***a) MIT-BIH ECG Dataset:*** This database [20] comprises 48 recordings of patients' heartbeats at 360 Hz. There are two ECG leads on each record. The dataset's characteristics are as follows:

- Total Samples: 1,09,446
- Sampling Frequency: 125Hz
- Number of Categories: 5
- Number of classes: 5 (N - 0, S - 1, V - 2, F - 3, Q - 4)

The synthetic streams were created by adding drifts at regular time intervals on a large number of instances. Generating evolving data streams has the benefit of introducing diverse concept shifts with varying periods.

**4.3 Performance metrics:**
The proposed AHO-based Deep CNN techniques were evaluated using the following critical parameters: accuracy, sensitivity, specificity, F1 measure, and precision. This section contains a quick summary of the performance metrics.

***4.3.1 Accuracy:*** The assessment of proximity between the estimated value and the standard value is known as accuracy. The accuracy is shown numerically as

$$A_{cc} = \frac{Tr_{ps}+Tr_{ng}}{Tr_{ps}+Tr_{ng}+\Gamma a_{ps}+\Gamma a_{ng}} \quad (1)$$

where $A_{cc}$ is the accuracy, $Tr_{ps}$ is the true positive value, $Tr_{ng}$ is the true negative, $\Gamma a_{ps}$ is the false positive, and $\Gamma a_{ng}$ is the false negative values.

***4.3.2 Sensitivity:*** Sensitivity refers to the overall number of true positive values correctly detected by the system. The system's sensitivity is expressed numerically as,

$$Se_n = \frac{Tr_{ps}}{Tr_{ps}+\Gamma a_{ng}} \tag{2}$$

***4.3.3 Specificity***: Specificity refers to the total number of real negative values correctly detected by the system. The system's specificity is mathematically described as,

$$Sp_e = \frac{Tr_{ps}}{Tr_{ps}+\Gamma a_{ng}} \tag{3}$$

***4.3.4 Precision***: The term precision denotes how close the two measurements are to one another.

$$pr_e = \frac{Tr_{ps}}{Tr_{ps}+\Gamma a_{ps}} \tag{4}$$

***4.3.5 F1-measure***: The F1-measure is estimated using the following equation.

$$F1 - measure = \frac{2Tr_{ps}}{2Tr_{ps}+\Gamma a_{ps}+\Gamma a_{ng}} \tag{5}$$

**4.4 Experimental evaluation**:

The proposed AHO-based Deep CNN approach focuses on identifying ECG abnormality types from data streams. For the evaluation of the models, the prequential and hold-out validation models are used. During the hold-out validation phase, ten percent of the sample data is used as the first training set. The remaining 90% of the data is used as a test set for online training. For online training, the prequential validation phase, also known as test and train validation, is used, in which the input instance is used first for the test model and then for the updating model. In this study, key parameters, including accuracy, precision, sensitivity, precision, and F1 score, are used.

**4.5 Comparative models:**

For the comparative analysis, eight models, such as Multi-Layer Perceptron [21], Support Vector Machine [22], Random Forest [23], AdaBoost [24], K-nearest neighbor [25], Deep-CNN [26], SLO-based Deep CNN [26] [18], COA-based Deep CNN[26][19] are utilized in this research

**4.6 Comparative discussion:**

The comparative discussion of the conventional and the proposed AHO-based Deep CNN is elaborated in this section. The comparative evaluations are accomplished by evaluating the parameters, such as accuracy, sensitivity, specificity, F1-measure, and precision, using the datasets, such as the seizure recognition dataset and MIT-BIH dataset. Table 1 demonstrates the comparative discussion of the methods for the 90% of training. The accuracy of the proposed model is observed as 98.63% and 98.4214%, respectively, for the two datasets with 90% of training, which shows that the proposed AHO-based Deep CNN outperforms all the other existing drift adaption methods. Figures 3, 4, and 5 provide a comparison of several parameters, such as accuracy, sensitivity, and specificity on the MIT-BIH ECG dataset.

**Table 1.** Comparison table based on the performance measures

| Methods | MIT-BIH ECG Dataset | | |
|---|---|---|---|
| | Accuracy (%) | Sensitivity (%) | Specificity (%) |
| MLP | 82.74% | 84.22% | 84.94% |
| SVM | 84.58% | 86.61% | 85.82% |
| RF | 80.08% | 82.55% | 79.24% |
| AdaBoost | 90.37% | 89.14% | 90.74% |
| KNN | 91.00% | 92.22% | 92.74% |
| Deep-CNN | 92.35% | 93.41% | 93.45% |
| SLO-Deep LSTM | 92.89% | 91.10% | 92.13% |
| COA-Deep CNN | 93.87% | 92.54% | 93.21% |
| **Proposed AHO-Deep CNN** | **94.55%** | **95.78%** | **95.98%** |

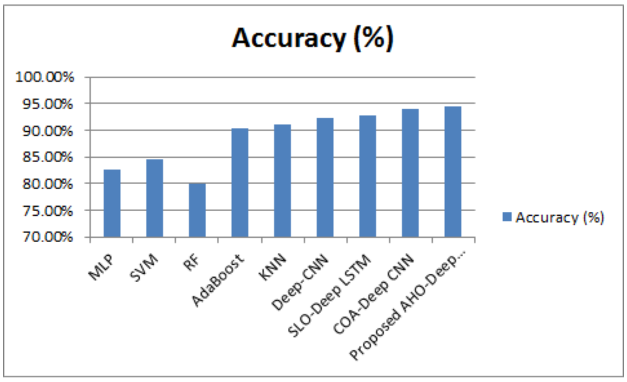


**Fig. 3.** Comparative analysis of Accuracy using MIT-BIH ECG Database

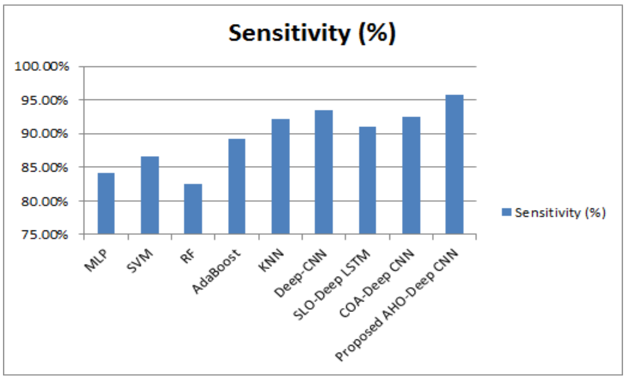


**Fig. 4.** Comparative analysis of Accuracy using MIT-BIH ECG Database

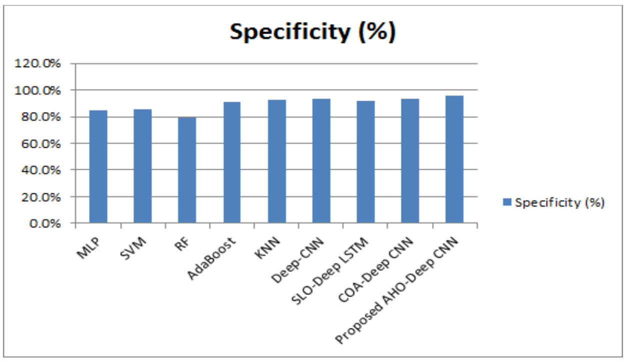


**Fig. 5.** Comparative analysis of Accuracy using MIT-BIH ECG Database

## 5. Conclusion

A method for handling the concept drift issues in online data streaming is proposed in this research, which involves offline learning and incremental learning. This research develops the dynamic streaming data analytic framework based on the optimized Deep CNN classifier and OASW approach that effectively addresses both memory and time constraints. The concept drift in the online data streams is effectively predicted using the proposed approach, and the proposed optimized Deep CNN classifier as a base classifier establishes the trained model for handling the offline learning process. The effectiveness of the research relies on the proposed nature-inspired algorithm known as the Aggressive hunt optimization algorithm, as it effectively trains the classifier to boost its performance. Moreover, an optimized adaptive and sliding window (OASW) is utilized in this research to adapt the pattern changes in the data streams during the incremental learning. The experimental analysis with the comparative methods based on the performance metrics is found to be effective with an accuracy, sensitivity, specificity, F1 score, and precision of 94.55%, 95.78%, 95.98%, 96.47%, and 96.87%, respectively.

We compared our method to a few different drift detection methods. Due to time restrictions, we were unable to compare all of the methodologies from similar investigations. We can perform other studies in the future to compare our effective methods to other relevant research. In future work, the ensemble classifier will be employed to train the more complex data.



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