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Chaser Priori Wolf (CPW) Optimization an Improved Optimization Technique Video Content Classification and Detection

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Abstract: Optimizers play a crucial role in video object detection by promoting the training and improving the performance of the model. Optimizers are responsible for minimizing the loss function during training. The parameters of models are updated iteratively based on the gradients of the loss parameters. By continuously adjusting the parameters in the direction of the steepest descent, optimizers guide the model towards convergence, reducing the loss and improving the object detection performance. In the proposed paper hybrid optimizer named chaser priori wolf optimizer is proposed. The chaser priori wolf optimization is based on the hybridization of cat swarm optimization and coyote optimization. Well-known optimizers like SGD, ADAM, adagrad, adadelta and RMSprop are used as default optimizers by researchers. The proposed work introduced CPW optimizer which works for classification to improve the convergence and feature selection. The comparative result showed an increase in the performance of CNN based YOLO model. The results are compared concerning sensitivity, specificity and accuracy. Results clearly showed improvement in all performance metrics and the average improvement in comparison with state of art architecture is 10.3%.

Keywords: Cat Swarm Optimization, Coyote optimization, chaser priori wolf optimization, CPW.

I. INTRODUCTION

The traditional optimizer needs manual tuning of the learning rate and unable to work with sparse gradients. The SGD, RMSProp, Adagrad, Adadelta and ADAM are popular optimizers in classification and detection tasks. Out of all ADAM has shown better results in comparison with others. However, the increasing video data and demand for detection and classification tasks attract researchers to identify better optimization techniques. SGD shows slow convergence with complex data. Improper selection of earning rate leads to local minima with SGD. RMSProp (Root Mean Square Propagation) Keeping the moving average of the squared gradients for each weight is the fundamental tenet of RMSprop. Next, multiply the gradient by the mean square root. It gives inconsistent performance with different datasets. Adagrad works on the knowledge of past observations [1]. The accumulation of squared gradients of the parameters, results in diminishing learning rates over time. Adadelta is a stochastic optimization method which enables the per-dimension learning rate method for SGD. In paper [2] proposes the Adam optimizer, an adaptive gradient-based optimization algorithm that has gained significant popularity in deep learning. Adam combines momentum-based optimization methods and root mean square propagation (RMSprop) to provide efficient and adaptive learning rates for different parameters. However, a comparison with a new optimizer is needed.

In recent years many evolutionary optimization algorithms have been used for classification and detection tasks. In the proposed paper novel optimizer named Chaser Prairie Wolf (CPW) optimization is proposed which is based on cat swarm optimization and coyote optimization algorithm. Here, the prairie wolves' tendency to cooperate helps the chasers' decision-making. The enabled optimization helped to improve outcomes by successfully adjusting the classifier settings.

II. LITERATURE SURVEY

The cat swarm optimization(CSO) combined with quantum mechanics to avoid local optima, is used in photovoltaic power point tracking systems [1]. The CSO algorithm is used in many hybrid algorithm generations to increase search ability in solutions. The computational cost is reduced with the use of

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CSO [1][2]. The CSO is used to control individual solutions and update processes by adopting different terrains of objective functions. The modified CSO is proposed to boost the search strategy. A small sample probability model-based compact cat swarm optimization algorithm, improves the search capability for a potential global best solution and lowers computation costs [2]. However, the performance is measured in specific scenarios its scalability is not discussed. A two-stage detector-based novel class discovery network is proposed in [3]. The method is implemented on unlabeled datasets to check the detection accuracy and significantly improves the class detection in labelled and unlabeled datasets. However, the two-stage detector model increases computational cost [2][3]. Small sample probability model-based cat swarm optimization is proposed in [3]. A detailed comparison of the bio-inspired algorithm is shown in a paper which reflects that CSO algorithm on modification with precise features can give better results on a variety of problems [3] The proposed model enhanced the CSO algorithm by improving the tracing model process, by introducing variable mode ratio control strategy and incorporating focus boost search. strategy.

The object tracking proposed in the multi-stage includes the first stage as the preprocessing stage and the second stage deals with identifying multiple objects in frames. Modification in the seeking and tracing mode of CSO algorithm is done to calculate the cost function [4]. The updated version of the fitness-distance balance (FDB) and Levy flight in the coyote optimization algorithm (COA) is proposed in the paper [5], it shows improved search performance, global exploration capability, and local exploitation capability. However, a detailed analysis with real time database is not given in paper. The paper proposed a detailed comparison with other optimization algorithm and proved COYOTE results superior in comparison to others [5]. The Coyote optimization algorithm is based on the hunting behavior of coyote. It is a meta-heuristic approach for optimizing various problems. It keeps balance between exploration and exploitation in search spaces. Coyote optimization is applied in computer vision problems to locate and classify objects. It optimizes the efficiency of detection by reducing losses [5][6]. An optimization algorithm to avoid local optima stochastic global optimization technique is proposed in [6]. For continuous search-space problems, a new stochastic global optimization method is put forth in the paper. The suggested technique is a swarm-based approach that searches for the best answer using spherical bounds in a vector search space [6]. To handle limited optimization issues, the research suggests a novel version of multi-objective particle swarm optimization and differential evolution that includes new processes and integrates them with the latter [7-8].

In the literature survey, it is found that the nature-inspired optimization algorithms outperform known optimizers. The proposed work in on hybridization of CSO and COYOTE optimization to give better optimization for object classification and detection algorithms[9].

III. ALGORITHMS

A. *Cat Swarm Optimization (CSO)[7][8]*

CSO is a nature-inspired optimization algorithm which is inspired by the hunting behavior of cat family animals. Cat behaviors guided the search strategy to find the optimal solution. The population was initially divided into seeking and tracing mode based on specific mixture ratios. The algorithm iteratively updates the fitness values in memory to distributed cats until it finds the most suitable solution. The CSO algorithm includes two major steps namely seeking mode and tracing mode [1-5]. The seeking mode creates seeking memory pool and count of dimensions to change. The dimensions are changed in each copy to check the fitness of best chosen solution. The tracing mode in CSO is feature selection phase which is represented by the following formula,

$$Vk+1 = wt * Vk + a*b*(Xj - Xi) \quad (1)$$

Where Vk is the previous velocity at iteration k represents the feature selected earlier. Xi represents the previous iteration position for the I iteration. X_j represents new features in j dimensions. The constant value is given by a and b is a randomly generated number ranging from 0 to 1. The new feature selected by considering the latest position of cats is given by moving the cats to the latest best position *Xi+1*.

$$X_{i+1} = i + V_{k+1} \quad (2)$$

B. *Coyote optimization algorithm(COA)[9]*

Coyote optimization algorithm works on the concept of sharing social structure and behavior of coyote[10]. The position of coyote is used to select best best-suited feature. The COA calculates the cultural tendency of the pack based on the information from the coyotes. The uniform distribution of probability is used to select the random coyotes, and the values of δ_1 and δ_2. The calculation of δ_1 and δ_2 are shown in equations [3] and [4].

$$\delta_1 = \alpha^{p,t} - soc_{cr1}^{p,t} \quad (3)$$

$$\delta_2 = c^{p,t} - soc_{cr2}^{p,t} \quad (4)$$

In the above equation cr1 and cr2 represent random coyote packs. The values of δ_1 and δ_2 are taken with 'p' pack and 't' instance.

The new social condition for coyote is shown in the following equation,

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$$nsoc^{p,t} = soc_c^{p,t} + r_1.\delta_1 + r_2.\delta_2 \quad (5)$$

IV. PROPOSED ALGORITHM

A. *Chaser Priorie Wolf (CPW)*

The paper proposed a hybrid optimization algorithm for classification. The work is based on nature-inspired algorithm CSO and COA. The alertness of cats and precision of coyotes were used in feature selection. The work is divided into two modes seeking mode and tracing mode. The CPW algorithm is used to fine-tune the weights and reduce the cost function. The equation given below represents the feature selection formula,

$$\alpha = Ynp + soc \quad (6)$$

where Y is a random number between 0 and 1, Y_{np} designates the new box containing objects. soc denote the common features. For effective classification, the error occurrence must be decreased, which is accomplished here by turning on CPW optimization. The optimization approach separately modifies the learning rate for each network weight, as opposed to keeping a constant learning rate throughout the training. The weight indicates how the input will affect the output, and it is finely adjusted to produce an optimal result. Using this CPW technique also gets rid of the noise and bias that are present in the classifiers. The chaser needs to adjust its position using the correct angle and velocity in order to efficiently chase and capture the prey.

$$\delta = P_{C.j.new} + new\_soc_{dw}^{r,T} \quad (7)$$

$$\delta = \left(P_{C.j.old} + C_{vy.j}\right) + new\_soc_{dw}^{r,T} \quad (8)$$

$P_{C.j.new}$ represents the updated position of the chaser in dimension j at a specific time instance denoted by T, and the group of prairie wolves is represented by the symbol r. A detailed comparison of various optimizers is shown in Table 1.

Table 1: Comparison of various Optimizers

Optimization	Learning Rate	Convergence Speed	Strengths
SGD [14]	Manual tuning	Moderate	Low memory requirements
Adam [15]	Adaptive learning rate with momentum	Fast	Fast convergence, Efficient memory utilization
Adagrad [16]	Adaptive learning rates for each parameter	Slow	Effective for sparse parameters
Adadelta [18][19]	Adaptive learning rates without a learning rate parameter	Moderate	No explicit learning rate, Good for online learning
Coyote Optimization [10]	Adaptive learning rate based on confidence intervals	Fast	Robust convergence, Good for non-convex problems
Cat Swarm Optimization [1][2]	Combination of exploration and exploitation using a swarm of agents	Moderate	Effective for global optimization, Good for multimodal problems
Chaser Priori Wolf (CPW) Optimization (Proposed)	Adaptive learning rates with swarm intelligence	Fast	Multimodal support and robust for ensemble models

V. METHODOLOGY

In the video content detection task, the localization and classification of objects is a primary task. The hyperparameter tuning of CNN based model is a proven technique for performance improvement of the classifier. But, it works on precise selection of parameters. The traditional methods involve computational complexity. The CPW algorithm optimizes and reduces complexity. The proposed Chaser prairie wolf optimization is developed by the standard hybridization of the characteristics of the chaser and prairie wolves. The hybrid classifier with CPW and Deep CNN give better results. The steps involved in the process are shown in Figure 1.

The datasets used are MSCOC and PASCAL VOC. The COCO image dataset, comprising approximately 328,000 images, was specifically curated to enhance image recognition performance. This dataset is notable for its inclusion of challenging and exemplary visual data for various computer vision tasks. Within the COCO dataset, annotations encompass a range of tasks such as object detection, captioning, segmentation, and more. PASCAL VOC, on the other hand, serves as a standard benchmark dataset for addressing concerns related to object detection, semantic segmentation, and classification. This dataset consists of three subsets: a private testing set, which evaluation, along with 1,449 images

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designated for validation, and an additional 1,464 images allocated for training purposes.

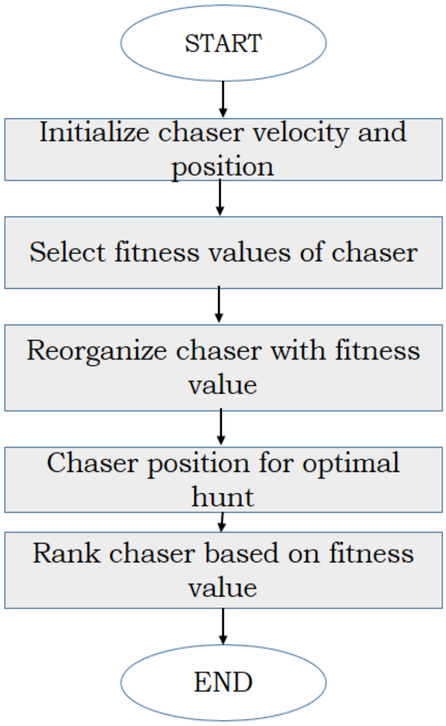

Figure 1. Methodology

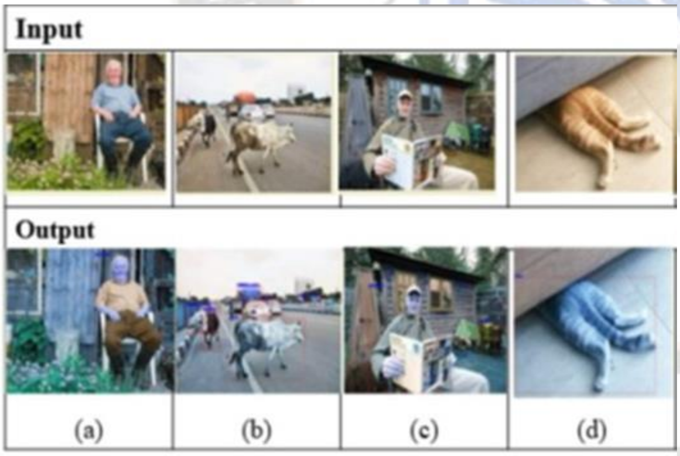

Figure. 2: Results (a) Object in the challenging background, (b) Multiple Objects in occlusion, (c) Occluded objects, (d) Object with more than 50 per cent of occlusion

VI. EXPERIMENTAL SETUP

On a Windows 10 computer with 8GB of RAM, the experiment was carried out using Python and the Keras library. The COCO dataset and the PASCAL dataset were both used in the implementation. Random video clips were utilized as test inputs to assess the model's performance.

VII. RESULTS

The proposed CPW optimizer is applied in YOLO V4 , the classification and object detection on various object conditions is shown in Figure 2. Figure 2 (a) to 2(d) shows various object positions in frames and images. The proposed model is successfully able to detect objects with occlusion, objects in frames with bad light conditions and objects with challenging backgrounds. The performance is measured using accuracy, sensitivity and specificity. With MSCOCO dataset the accuracy of content detection reaches up to 94 per cent for few classes and the average accuracy is 91 per cent. The average specificity achieved is 89 percent with an average sensitivity 89 percent. The learning rate used was 0.001 with 50 epochs. The training dataset was 80 per cent and 20 percent of dataset classes and the average accuracy is 91 percent. The average specificity achieved is 89 percent with an average sensitivity 89 percent. The learning rate used was 0.001 with 50 epochs. The training dataset was 80 percent and 20 percent of the dataset was used for testing. The average accuracy received with Pascal VOC dataset was 84 percent, the specificity received was 92 percent and the sensitivity received was 81 percent. The accuracy, sensitivity and specificity achieved with MSCOCO and PASCAL VOC dataset is shown in Figure 3 and Figure 4.

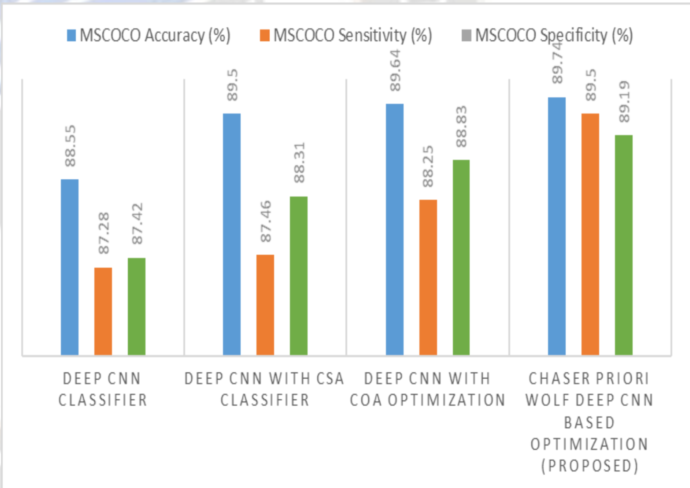

Figure 3: CPW optimizer implemented with Deep CNN and results are compared with other classification algorithms using MSCOCO dataset

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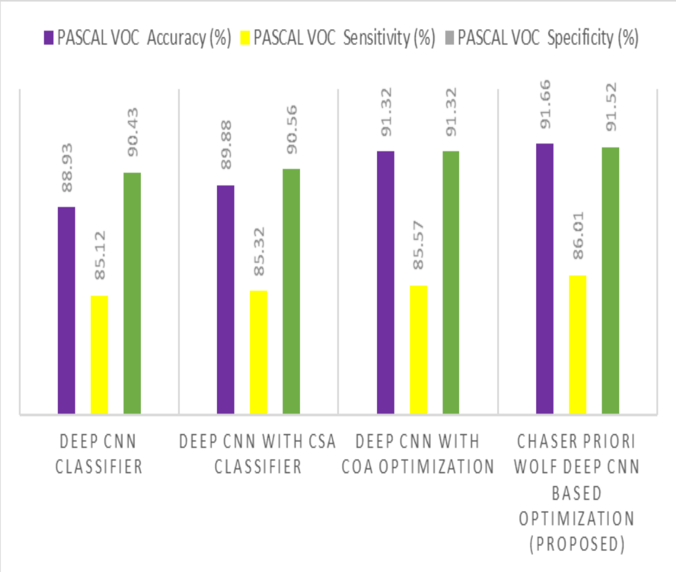

Figure 4: CPW optimizer implemented with Deep CNN and results are compared with other classification algorithms using PASCAL dataset

VIII.CONCLUSION

This proposed CPW optimizer is implemented with deep CNN classifier to tackle the task of object detection within video content. Video analytics furnish a wealth of vital insights and statistics pertaining to audience responses to such content. In this work, CPW optimization technique helps to optimize the classifier's parameters, producing better results in the end. With MSCOCO the performance metrics are 89.74% accuracy, 89.50% sensitivity, and 89.19% specificity. Even more impressively, PASCAL yields even higher efficiency with values of 91.66% accuracy, 86.01% sensitivity, and 91.52% specificity, underscoring the robustness and superiority of our approach. Practically, the applications of this model extend to real-time scenarios, including but not limited to watermarking, summarization, and video indexing for surveillance purposes. These versatile applications reflect the potential of our research to enhance various aspects of video content analysis and management.

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