

DESIGN OF BIO-INSPIRED ALGORITHM FOR OPTIMIZING THE FEATURE SELECTION PREPARED FOR CLASSIFICATION IN LIVER TUMOR DETECTION

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Abstract

Bio-inspired phenomena are mimicked and practised in searching problems to generate optimal solutions for the problem of escaping local minima convergence. In this article, we apply the advantage of this principle for reaching a set of better-performing classifiers under supervised learning to classify images showing liver Tumor occurrence. The proposed architecture tries such three different Meta-heuristic algorithms. Most of the previous works made feature selection and classification under two different tools and environments. Hence here the implementation of Image classification is preceded by Gabor Image Filtering and feature selection by three different species belonging to insect, bird and animal categories are done in the same tool with appropriate plug-ins managed. The primary result based on this proposed framework is obtained and shown in terms of Accuracy, Precision, ROC, F_Measure, and Recall and their maximum values are 87.93 %, 88 %, 94 %, 88 %, and 76 % respectively.

Keywords: Liver Tumour, Weka Packages, Classifier, Supervised Learning, J48, KNN, RF, RepTree, Gabor Filter, Bio-Inspired algorithms: Firefly, Rhinoceros, Cuckoo.

1. Introduction.

Bio-Inspired algorithms are manifested usually Metaheuristics [24] algorithms mainly contributing to the part in machine learning for searching significant attributes in the underlying dataset. In this aspect, they contribute a reasonable lift in the behavior of classifiers for medical imaging [12]. They are inspired usually by biological or various natural phenomena. The identification of subsets of attributes in a dataset may not be sometimes fruitful if the size of the original set is huge. In the case of medical image processing, it boils down to a filtered set of attributes, initially with a greater number of attributes demanding for search for a smaller and more significant subset. Researchers depend on a careful selection of metaheuristic approaches to yield optimal solutions for this problem [2,19].

Here, in particular, a relatively new category of search methods based on bio-inspired methods like Swarm Particle methods, and a similar set of methods realized as feature selection Package Library, is presented as an alternative to traditional search methods like greedy, best first or breadth-first genetic algorithms. This novel approach gives yet another combination for making trials and measuring results for feature selection followed by classification for Liver Tumor[7]. The followings are organized as follows: Section II represents the Related work; the next Section III describes the Data description of Liver Tumor; Section IV discusses the proposed model for feature extraction and their classification; Section V shows experiment results achieved by the proposed model. Section VI concludes the research.

2. Related Works

Du et al 2012 [2,9], the authors developed a mutation-based image matching version of the bat algorithm it is based on the echolocation behaviour of bats, superior to differential evolution and genetic algorithms. Yang et al 2021 [23,25], applied Firefly Algorithm based on flashing patterns, activity of tropical fireflies and the competitive movement of one firefly determine by the brightness of each one. Yang, Xin-She 2010 [24], the authors developed the bio-sonar features of microbats that were utilized in the traditional bat algorithm (BA) this type of algorithm can also efficiently tackle difficulties of large-scale through automatic zooming, frequency tuning, and parameter control. Waleed et al 2017 [21],[24], presented a broad overview of biologically inspired optimization algorithms and organized by the biological field that inspired them and dealt with many useful applications where they have proven to be most useful. Simon Fong et al 2018 [19], the author proposed nine swarming search algorithms to improve existing search methods and provide efficient and effective data mining feature selection. Yang et al. [2013] [25] used Firefly Algorithm (FA), the best performing technique due to its automatic generation of subdivisions. Hanane Menad et al 2018 [11] the author used 4 different bio-inspired algorithms on 7 medical datasets and the results demonstrated good supervised classification accuracy and two of the algorithms were based on similarity calculations. Rodrigues et al 2016 [8], the author examined the Cuckoo Search in order to optimize Deep Belief Networks (DBN) for the task of binary image reconstruction. Moreover here, the DBN was compared with 2 different datasets as well as the next levels were examined and the three layers obtained good results.

3. Material and Methods

This section introduces the methodology used to design the general approach in addition to the used dataset as well as the features-based classification.

3.1 Different types of Classifiers

3.1.1 J48

The J48 algorithm is one of the machine learning algorithms which is used for classification [20]. J48 is used for partitioning into bins of data satisfying the conditions as labels on the branches of the decision tree. The medical image data for Liver Tumor is evaluated by J48 and comes under in decision tree for classification. The readability or interpretation of results are straight forward in the case of decision tree classifiers. In industries, the decision trees are followed most of the time due to its simplicity. The construction of such trees mainly depends on selection of attributes yielding more information gain and this step consumes maximum complexity in each iteration.

3.1.2 Random Forest

Random Forest, by its name imply random subset of decision trees at each iteration generates classification results and finally it is integrated. Greater the number of trees in these subsets, the results namely the accuracy can be enhanced tremendously and prevents the problem of over fitting. It is an ensemble type of classifier, bagging filled with trees. When compared to other applied classification algorithms, the Random Forest (RF) classifier aids in the automatic detection of Liver Tumor and delivers good accuracy results. Breiman created RF, which is a powerful and novel statistical classifier [3]. It has a number of advantages over other classifiers, including a new technique for instance and to develop the model prediction and it involves different functions including unsupervised learning, regression, and survival analysis, classification, [6]. The random forest structure has proven to be useful for both regression and classification.

3.1.3 KNN

The KNN implementation of the instance-based nearest neighbour [5] is based on Euclidean measure with easier steps for imitating the neighbours which is computationally expensive. This is achieved by a straightforward approach that is applied to classifications. We assessed the average forecast accuracy and variance of accuracy for various k values ($k = 1, 2, \dots, 30$), and then chose the optimum k number by compromise based on the principle of maximum accuracy and minimal variance[13]. Being based on the non-parametric algorithm, there is no need to look for underlying data distribution. Moreover, this algorithm happens to be 'lazy' as each time it does not depend on any training set, but only the local neighbour set of nearest data points with set size maximum k. Similarity or distance measure mainly used in this algorithm places a primary role to classify the instances.

3.1.4 SVM

SVM is one of the supervised machine learners [1] and is used to address accuracy in classification problems. The boundary hyper line generated with possible marginal value on both sides shows maximum width enclosed by special data points termed as 'support vectors. This is also as above algorithms, applied to solve problems of classification as well as regression[4]. Hyperspace makes the data points transformed so that it is easier to classify by hyper line or hyper plane. From the set of Kernels for this transformation is fixed at the beginning itself. The success rate found in this algorithm enables us to find best results in most of the times for Face detection, image classification, text categorization, etc.

3.1.5 RepTree

Similar to J48 algorithm, REP Tree is based on error pruning and reduction of variance in each iteration. This also makes use of information gain as the measure of each attribute for building the tree. Missing values for numeric values are tackled efficiently by this algorithm.

3.2. Bio-Inspired Search Optimization Algorithms

Here three types of search methods are considered each in different species.

3.2.1 Firefly Search

The basic procedure for the firefly algorithm is Fireflies [26] are unisexual, which means that regardless of sex, one firefly will be attracted to another firefly. Attractiveness and brightness are proportionate, and both decreases as distance rise. As the result, they are two different flashing fireflies, based on the brightness which move randomly. The objective of the firefly algorithm is to determine the brightness [11] of the firefly Application of Firefly algorithms are, Digital picture compression and image processing, Feature selection and defect detection

3.2.2 Cuckoo Search

The cuckoo bird search for a suitable place to lay eggs within her radius of the egg-laying. This process happens continuously until it finds the best place with the largest profit found. Each cuckoo lays one egg based on the randomly selected nest. [18]

3.2.3 Rhinoceros Search

This paper proposes a rhinoceros search mechanism (RSA) [10] based on the rhinoceros' natural behaviour. The RSA abstracts and simplifies the foraging and other natural activities of rhinoceros in groups. RSA also demonstrates its strength in solving high-dimensional optimization issues. Furthermore, RSA is substantially faster than ESA. Some assumptions are made based on rhinoceros' behaviour to ease the working process, In their search range, all agents are conducting levy flights (pre-defined). Male agents have a bouncing mechanism, but female agents do not. Every epoch, there is a 0.05 chance that every agent will die and a rebirth mechanism will be established. This assumption disregards the group leader in favour of computation speed [27].

3.2 Gabor Filter

Gabor filter is a sequential filter, this filter plays an important role in medical image processing. Gabor Filter is used for feature extraction in image processing [20], and also process texture analysis, etc. In this research work, the Liver Tumor image dataset was extracted with Gabor filter. Gabor Filter converts the images from pixel to numerical data. The Gabor filter has sixty-one -61 Features [17].

3.3 Resample

Manages the random dataset without or with replacement. Produces a random subsample of a dataset with or without replacement sampling. The complete original dataset must fit in memory[20]. It is possible to specify the number of instances in the created dataset. A nominal class attribute must be present in the dataset.

3.4 Attribute Selection

After feature extraction, feature selection is a crucial stage to explore for ways to enhance accuracy and reduce training and testing errors [22]. To create a successful machine learning model, it's critical to remove unnecessary attributes from the database. There are automated feature selection tools available[2]. Finally, the classification stage, different types of classification methods are compared with each other and obtained good results

3.5 Performance analysis:

The performance analysis is derived from the Predicted values which are available in the confusion matrix. Totally it has 4 predicted values such as True Positive(TP), False Positive(FP), False Negative(FN), and False Negative (FN).

$$\text{Specificity} = \frac{\text{Number of True Negative}}{\text{Number of True Negative} + \text{Number of False Positive}} \dots\dots\dots(1)$$

$$\text{Accuracy} = \frac{\text{Number of True Positive} + \text{Number of True Negative}}{\text{Number of True Positive} + \text{Number of False Negative} + \text{Number of True Negative} + \text{Number of False Positive}} \dots\dots\dots(2)$$

$$\text{Precision} = \frac{\text{Number of True Positive}}{\text{Number of True Positive} + \text{Number of False Positive}} \dots\dots\dots(3)$$

$$\text{Recall} = \frac{\text{Number of True Positive}}{\text{True Positive} + \text{False Positive}} \dots\dots\dots(4)$$

$$\text{F-Measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \dots\dots\dots(5)$$

4. Dataset Description

The public repository ‘Kaggle’ [14] provides the underlying dataset with “Liver Tumor Segmentation-130CT Scans” which contains 58,638 images, being obtainable in PNG format and readily available for data pre-processing. The resolution of each image happens to be 256 X 256. Kaggle provides a big set of high-resolution Liver Tumor images that were taken. These images are labelled and available as different types of Tumours and they are put under the class label as normal or abnormal as in Table 1.

INSTANCES	COUNT	LABEL	CLASS	ATTRIBUTE
58,638	51524	True	Normal	2
	7114	False	Abnormal	

Table 1- Liver Tumor Dataset Description

4.1 Tool description

WEKA is a data mining tool for developing the different algorithms and WEKA is developed by Waikato University in New Zealand. It has a set of machine learning algorithms. WEKA contains Pre-processing, classification, Cluster, Associate, and Visualize. In addition to that, the package manager can also be used to create new machine learning methods. [22]. An academic tool which has been used for research and industrial product transfer and verification is available in the Java platform and delivered with extra packages in Weka 3.8.1. This tool includes image filtering, and feature extraction, as well as dealing with texture characteristics. Procedural steps are meant for images combined with one-fold and used to build an ARFF (Attribute-Relation File Format) file with two attributes: file name and class label. With various forms of image filters, the image filter ‘Gabor Filter’ appears in the list of unsupervised instance filters. This version of WEKA has a total of ten different image filters. Depending on the application's needs, we apply the appropriate filter to alter the input image.

5. Experimental Setup and Results

This section discusses the experimental setup using the tool WEKA 3.8.1 for constructing the proposed framework figure 4 shows various bio-inspired algorithms. The results are enumerated under 3 types of from the family’s insect, bird and animal with specific instances namely Firefly, Cuckoo, and Rhinoceros respectively.

Based on the above architecture the experiment is set up with 10 folded cross validation. From the Gabor filter as in 3.2 the extracted features are imported as an input to different classifiers, Random Tree, Support Vector Machine (SVM), J48, K-Nearest Neighbour, REPTree, and Random Forest. Tables 2,3,4, illustrate the performance measures values of applying the classification methods over extracted features. The results indicate the J48 produced highest values, 87.91 for accuracy in all the bio-inspired algorithms.

5.1.1 Cuckoo Search

CLASSIFIER	ACCURACY	PRECISION	RECALL	F-MEASURE	ROC
Random Tree	82.39	0.823	0.824	0.824	0.586
Random Forest	87.03	0.84	0.87	0.849	0.733
KNN	87.56	0.838	0.876	0.844	0.653
REPTree	87.83	0.839	0.878	0.84	0.732
SVM	87.86	0.879	0.879	0.935	0.5
J48	87.91	0.841	0.879	0.827	0.593

Table 2. Performance Analysis of Cuckoo Search

Table 2 shows the 21 features reduced from 61 features of Gabor features of the images in the input image set the accuracy range we observed in the context of Cuckoo Search is 82.39 to 87.91. The precision ranges from 0.823 to 0.879. The recall ranges starting from 0.824 to 0.879, The F-Measure ranges from 0.84 to 0.935 and the ROC ranges from 0.5 to 0.733.

5.1.2 Firefly Search

CLASSIFIER	ACCURACY	PRECISION	RECALL	F-MEASURE	ROC
KNN	83.3845	0.833	0.834	0.833	0.605
Random Tree	87.0135	0.839	0.87	0.849	0.732
Random Forest	87.1227	0.841	0.871	0.849	0.732
REPTree	87.8304	0.839	0.878	0.84	0.723
SVM	87.8969	0.839	0.879	0.825	0.689
J48	87.9327	0.842	0.879	0.828	0.606

Table 3: Performance Analysis of Firefly Search

Table 3 represents, with the 25 features reduced from 61 features of Gabor features of the images in the input image set the accuracy range we observed in the context of Firefly Search is 83.38 to 87.93. The precision ranges from 0.83 to 0.841. The recall ranges starting from 0.83 to 0.879, The F-Measure ranges from 0.83 to 0.894 and the ROC ranges from 0.605 to 0.732.

5.1.3 Rhinoceros Search

CLASSIFIER	ACCURACY	PRECISION	RECALL	F-MEASURE	ROC
Random Tree	82.38	0.825	0.824	0.824	0.591
Random Forest	87.0221	0.84	0.87	0.849	0.733
REPTree	87.7946	0.838	0.878	0.839	0.723
KNN	87.8151	0.842	0.878	0.844	0.758
SVM	87.8679	0.879	0.879	0.935	0.5
J48	87.9037	0.839	0.879	0.827	0.588

Table 4: Performance Analysis of Rhinoceros Search

Table 4 shows 26 features reduced from 61 features of Gabor features of the images in the input image set the accuracy range we observed in the context of Cuckoo Search is 82.38 to 87.90. The precision ranges from 0.825 to 0.879. The recall ranges starting from 0.824 to 0.879, The F-Measure ranges from 0.824 to 0.935 and the ROC ranges from 0.5 to 0.758.

5.2 Proposed Method

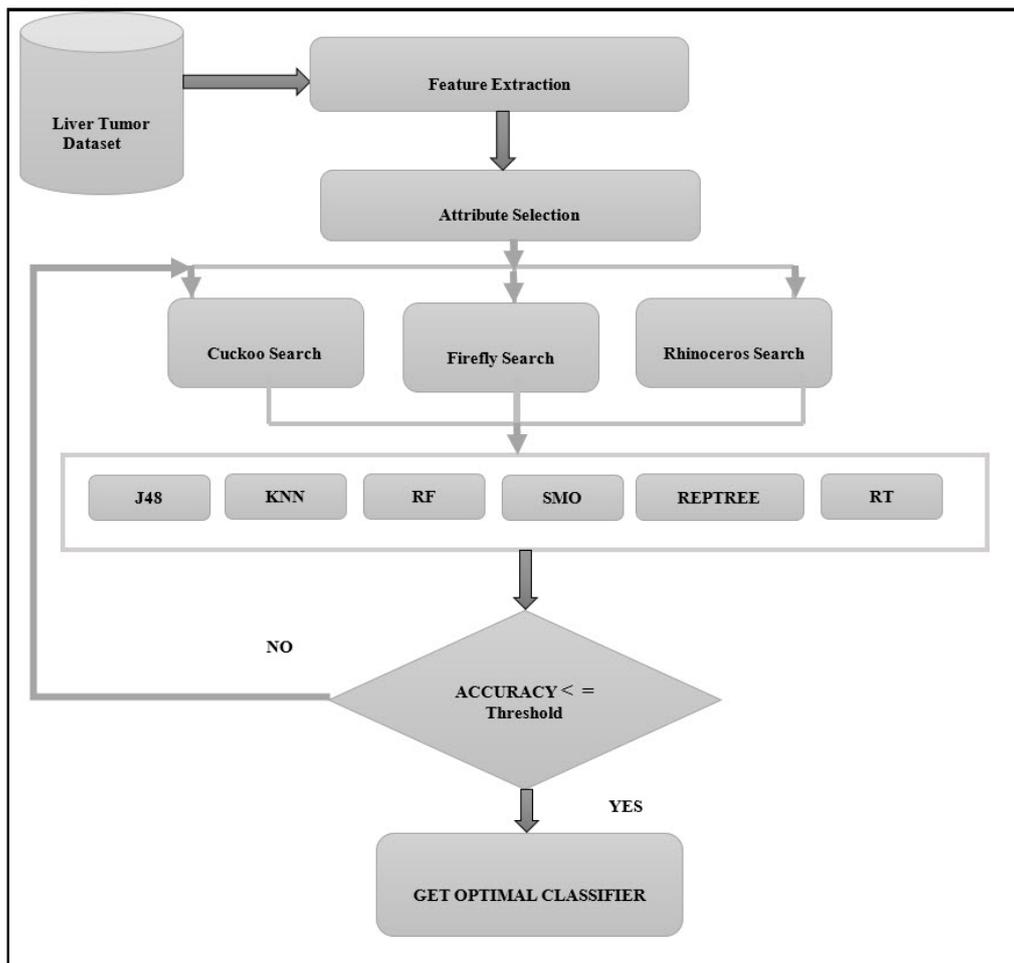


Fig. 1. A schematic view of the Proposed Model

Figure 1 depicts the methodology diagram for the proposed framework for the experimental setting. This figure depicts the steps that must be followed to obtain the optimal learning model for classifying Liver Tumor images. The pixel images, each has got 256 * 256 resolution. These images are filtered for feature extraction, embedded with Gabor filter. The numerical values thus obtained by these embeddings are pipelined with three bio-inspired algorithms namely Cuckoo algorithm, Firefly algorithm and Rhinoceros algorithm. Then the dataset with restricted or filtered attributes are sent for classification of types: decision trees[16], instance based, regression based, and ensemble of trees. No iterations are carried out with the limiting criteria on accuracy, an important performance prescribed with an expected threshold. If the loop converges then the classifiers are recommended with top performance as stated in the result section.

In the proposed experiment the data collection consists of liver tumour image set with the data distribution 7114 instances affected and 51524 not affected. This training set is used partially as testing test in the ratio 80 and 20 percentage.

5.3 Performance Results

In the procedure for selecting the category of classifiers, we fix the member of the category and its default parameters and then execute the training and training in cascade with 10-fold cross-validation. This is iterated for other categories and repeated for each classifier in each category. The findings are tabulated for each iteration's considerably greater accuracy values.

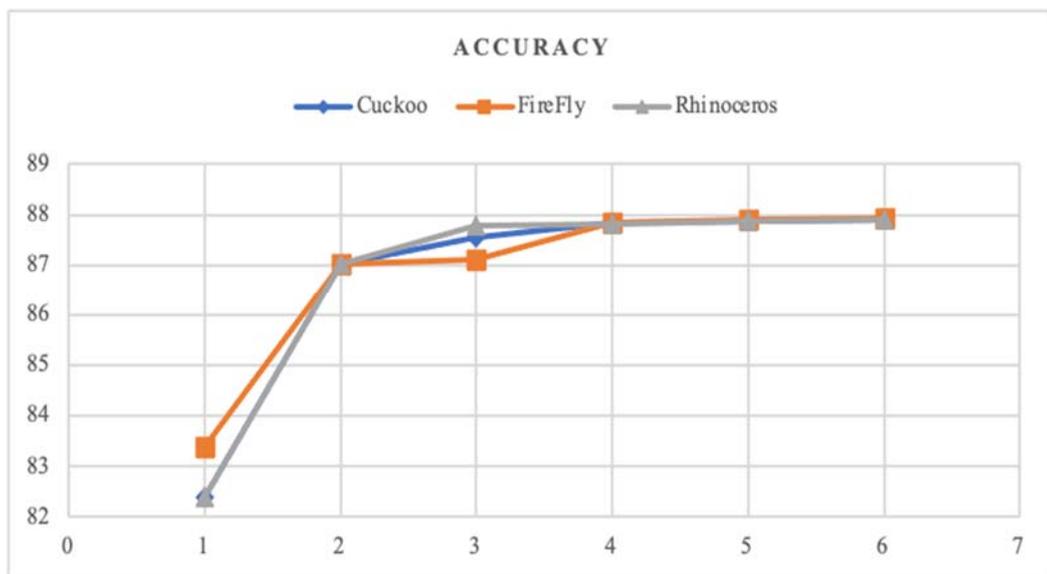


Fig.2. Accuracy Curve Analysis

Figure 2 contains the performance metrics with three different bio-inspired search methods like Cuckoo, Firefly, and Rhinoceros with Accuracy curve.

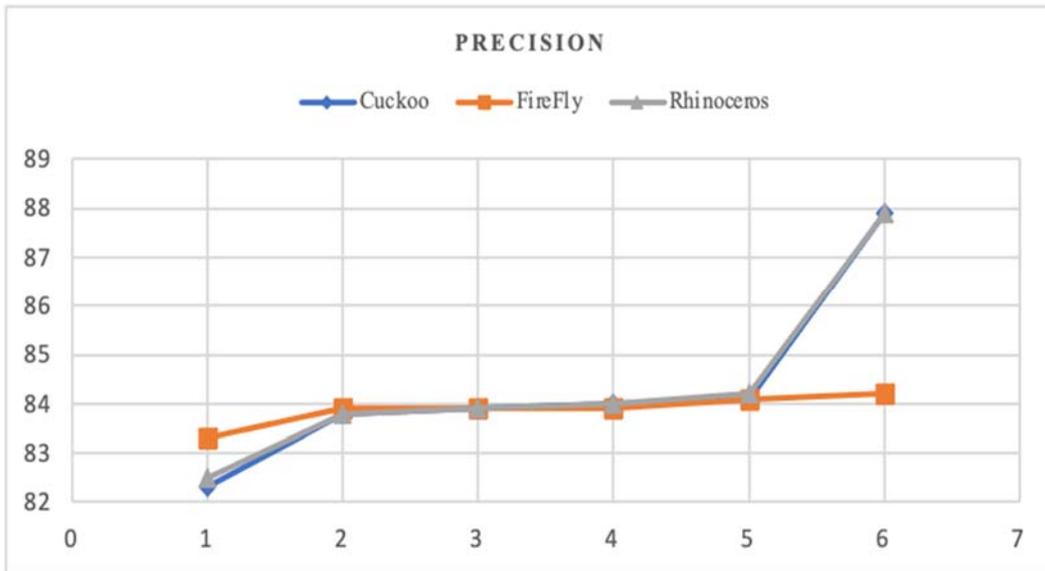


Fig.3. Precision Curve Analysis

Figure 3 represents the performance metrics with different bio-inspired search methods like Cuckoo, Firefly, and Rhinoceros with Precision.

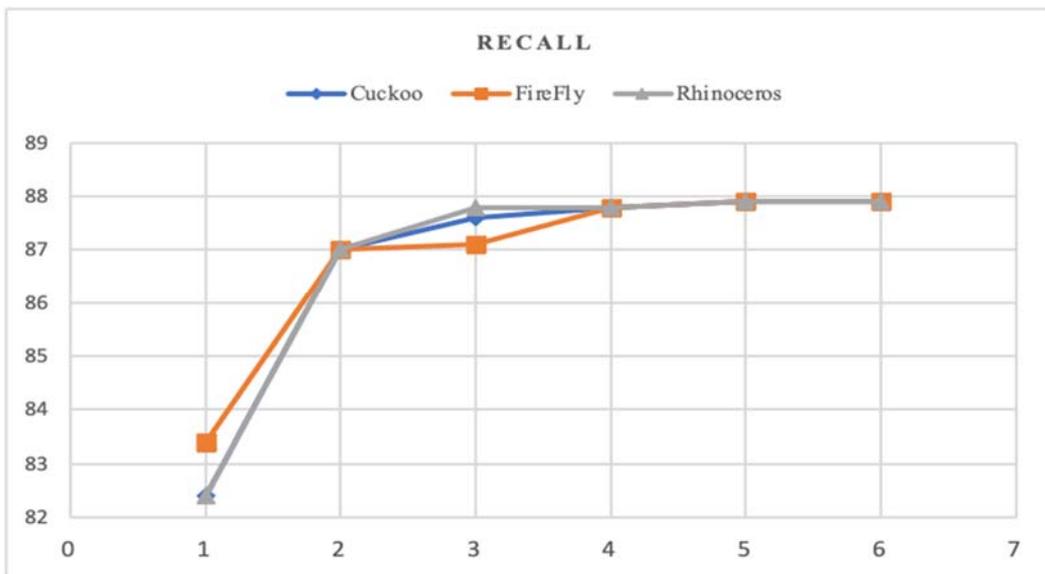


Fig.4. Recall Curve Analysis

Figure 4 represents the performance metrics with different bio-inspired search methods like Cuckoo, Firefly, and Rhinoceros with Recall.

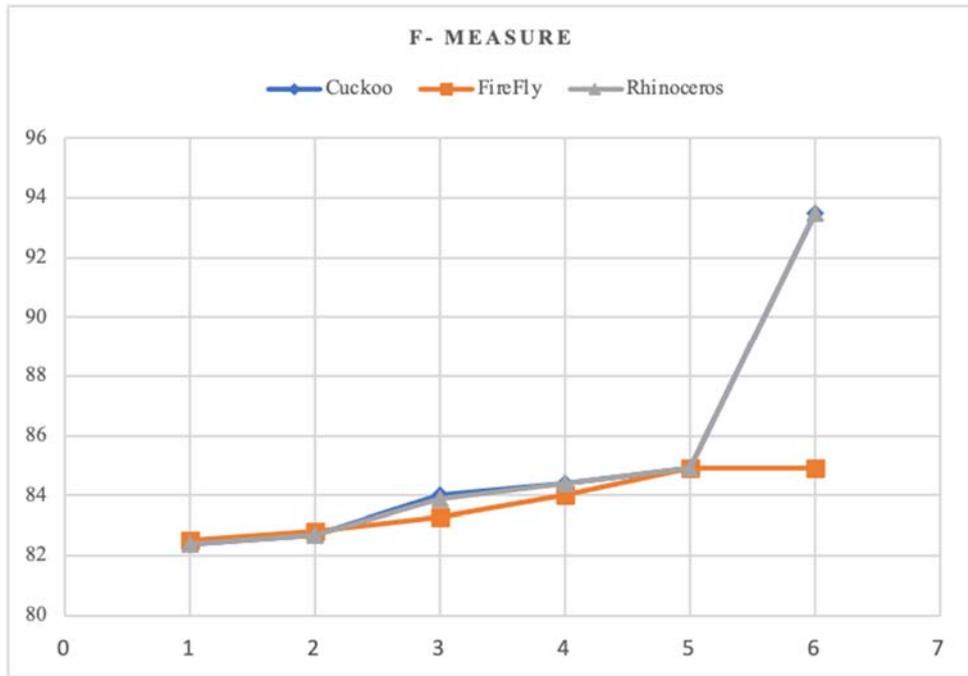


Fig.5. F_Measure Curve Analysis

Figure 5 represents the performance metrics with different bio-inspired search methods like Cuckoo, Firefly and Rhinoceros with F_Measure Analysis.



Fig.6. ROC Curve Analysis

Figure 6 represents the performance metrics with different bio-inspired search methods like Cuckoo, Firefly, and Rhinoceros with ROC Curve.

5.3.1 Classified instances counts determined by Cuckoo algorithm

SNO	CLASSIFIER	TRUE NEGATIVE	FALSE POSITIVE	FALSE NEGATIVE	TRUE POSITIVE	SENSITIVITY TP/TP+FN	SPECIFICITY TN/TN+FP	KAPPA STATISTIC
1	RandomTree	49633	1891	5724	1390	0.195	0.963	0.2067
2	Random Forest	49633	1891	5724	1390	0.195	0.963	0.2067
3	KNN	46713	4811	4932	2181	0.306	0.906	0.2149
4	REPTree	50859	665	6471	643	0.099	0.987	0.1195
5	DT	51402	122	6997	117	0.016	0.997	0.0241
6	J48	51376	148	6928	186	0.026	0.997	0.0395

Table 5 : Performance Analysis metrics for Cuckoo Algorithm

Table 5 depicts the classification counts, confusion matrix with specificity and sensitivity and also measures the performance of the models.

5.3.2 Classified instances counts determined by Firefly algorithm

SNO	CLASSIFIER	TRUE NEGATIVE	FALSE POSITIVE	FALSE NEGATIVE	TRUE POSITIVE	SENSITIVITY TP/TP+FN	SPECIFICITY TN/TN+FP	KAPPA STATISTIC
1	RandomTree	46386	5138	5188	1926	0.270	0.900	0.1715
2	Random Forest	49619	1905	5700	1414	0.198	0.963	0.2101
3	KNN	46714	4810	4933	2181	0.30	0.906	0.2148
4	REPTree	50863	661	6471	643	0.09	0.987	0.1197
5	DT	51418	106	7008	106	0.015	0.997	0.0221
6	J48	51389	135	6950	164	0.023	0.997	0.0348

Table 6 : Performance Analysis metrics for Firefly Algorithm

Table 6 depicts the classification counts, confusion matrix with specificity and sensitivity and also measures the performance of the models.

5.3.3 Classified instances counts determined by Rhinoceros algorithm

SNO	CLASSIFIER	TRUE NEGATIVE	FALSE POSITIVE	FALSE NEGATIVE	TRUE POSITIVE	SENSITIVITY TP/TP+FN	SPECIFICITY TN/TN+FP	KAPPA STATISTIC
1	RandomTree	46295	5229	5103	2011	0.394	0.898	0.1798
2	Random Forest	49627	1897	5713	1401	0.245	0.963	0.2083
3	KNN	46714	4810	4933	2181	0.442	0.906	0.2148
4	REPTree	50849	675	6482	632	0.097	0.986	0.1168
5	DT	51402	122	6997	117	0.016	0.997	0.0241
6	J48	51387	137	6956	158	0.022	0.997	0.0333

Table 7 : Performance Analysis metrics for Rhinoceros algorithm

Table 7 depicts the classification counts, confusion matrix with specificity and sensitivity, and also measures the performance of the models.

6. Conclusion

A wide impact on next-generation computing is made by Bio-inspired algorithms as they are emerging as the most powerful algorithms for optimization. The instances of collaborating Machine Learning models for their parameters being selected by Bio-inspired algorithms are visible in the fields of computer science, biology, ecology, social science etc. and working towards much more significant and outstanding results. The state of the art about parameter optimization for deep learning with Bio-inspired algorithms considered to make an investigation through three optimization methods and made open for further scope. Hence this article contributes yet another instance of optimization in medical imaging but exclusively for the application of detecting the occurrences of liver Tumor. The three species namely insect, bird and animal-oriented set of bio-inspired algorithms, KNN, SVM, RF, RT, RepTree, J48, and J48 enable the classifier to generate a maximum of 87.9037 accuracies respectively. The same results can be extended for other medical imaging requirements with different modal types

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Statement on No conflict of interest:

There is no conflict of interest among the Authors of this Article

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