krill Herd Algorithm (KHA). KHA is a streamlining technique to tackling enhancement issues that depends on krill herd swarms of organic and ecological forms.

3.1 Krill Herd Algorithm (KHA), initialization

The main parameters of the Krill Herd Algorithm(KHA) are the total evolution number, the population size, D^{max} (Maximum induced motion), S_f (Sensing factor), r_t (Random number) and R_D^{max} (Maximum diffusion speed). In this technique, Krill Herd represents the features value.

3.2 Fitness calculation

Evaluate the fitness utility depends on the maximum accuracy and moreover select the finest result.

Fitness = Max(accuracy)

three movement of each individual krill are,

(a) krill individuals Development,

(b) Foraging action,

(c) Random dispersion.

3.3 Development initiated by other Krill individuals

Speed of every krill individual is impacted by the development of the other Krill's to keep up a high thickness. Three impacts namely neighborhood impact (x), target impact (y) and repulsive impact (z) are used to evaluate the direction of motion induced (ξ_m). Krill individual motion may be formulated as

$$D_m^{new} = \xi_m D^{\max} + \chi_b D_m^{old} \quad (1)$$

The sensing distance S_d between the individual krills and the neighbors formulated by,

$$S_d = \frac{1}{5N}\sum_{n=1}^{N-1}\left|F_m - F_n\right| \quad (2)$$

3.4 Foraging action

The foraging velocity of m^{th} krill individual can be expressed by

$$F_{Fm}^{new} = S_f \varsigma_m + \chi_x F_{Fm}^{old} \quad (3)$$

3.5 Random dispersion

To enhance the population diversity random diffusion process is mainly considered and it is expressed by

$$R_{Dm}^{new} = \beta \times R_D^{\max} \quad (4)$$

3.6 Updating the krill position

In updating the position, the individual krill changes its present positions also, moves to better positions in light of induction movement, foraging movement and random dispersion movement. In this three movements, the upgraded position of the m^{th} krill individuals during the interval of t and Δt might be communicated by

$$P_m(t+\Delta t) = P_m(t) + \Delta t \frac{dP_m}{dt} \quad (5)$$

Based on the above procedure, we select the optimal features and then the selected features are fed to the classification process.

3.7 Classification using Hybrid Adaboost KNN algorithm

Finally, the optimal features are furnished to Hybrid Adaboost KNN classifier for the purpose of classification.

3.8 Hybrid Adaboost KNN algorithm

Hybrid Adaboost technique combine multiple "weak classifiers" into a single "strong classifier". Each weak classifier should be trained on a random subset of the total training set. Adaboost assigns a "weight" to each training sample, which determines the probability that each sample should appear in the training set. After training a classifier, Adaboost increases the weight of the classifier. All the learners are simple and weak and must have error less than 0.5. Otherwise, the process is stopped since its continuation makes the learning become difficult for the next classifier. Also, the initial probability of selecting sample is considered to be uniform. In fact, the weight of sample shows the importance of the sample. The final hypothesis is obtained through weighted voting of T number of weak hypotheses. The steps involved in this algorithm are shown below.

Step 1: Initialization of weight W

Step 2: In the case, $t \leq Tanderr^t < 0.5$, then normalize weight W^t, so that, $\sum_{t=1}^{N} W_i^t = 1$

Step 3: Call KNN, providing with the weight W^t, get hypothesis $h^t: X -> \{-1,1\}$

3.9 Krill Nearest Neighbor (KNN) classifier

The KNN calculation is a strategy which is utilized for characterization of any items or different components dependent on the nearest preparing information which are accessible in the element space. The qualities closest to the Krill esteem will be picked for the characterization results. When the grouping of closest neighbor is done, convert it into vector esteems with fixed length by using the Euclidean separation work in KNN which is given in beneath articulation,

$$E_D(x,y) = \left(\sum_{k=1}^{N}(x_k - y_k)^2\right)^{\frac{1}{2}} \quad (6)$$

where x, y are feature values;

The premise of the KNN classifier is the little neighborhood in the comparable highlights. These procedures will give better exactness in arranging the outcomes.

Step 4: Compute $err^t = \sum_{i=1}^{N} W_i^t e_i^t$,

Where $e_i^t = 1$, if $h^t(x_i) \neq v_i$, and 0 otherwise

Step 5: Set $\alpha^t = 0.5\log[(1-err^t)/err^t]$

Step 6: Update the weights to be as follows,

$W_i^{t+1} = W_i^t \exp(2\alpha^t e^t)$

Step 7: Put $T = t+1$ and the process repeats until $err = 0$.

After every classifier is prepared, the classifier's weight is determined dependent on its exactness. Increasingly precise classifiers are given more weight. At long last we characterize the medicinal information with high precision esteem.

4. RESULTS AND DISCUSSION

The Case Study of Medical classification is implemented using Python software and the experiment is done using i5 processor with 3GB RAM.

4.1 Dataset description

4.1.1 Mammographic mass data set

These datasets are taken from the UCI machine learning repository. The database comprises of around 2,620 cases.

For each case, dual images of every breast, inter related patient information, like age, period of the tumor, subtlety rating for varieties from the standard, American College of Radiology (ACR) breast thickness rating are considered. The Mammograms are digitized by various scanners depending upon the wellspring of the data.

4.2 Evaluation metric

The evaluation metrics used here contains True Positive, True Negative, False Positive and False Negative, Sensitivity, Specificity and Accuracy.

$$Sensitivity = \frac{T(P)}{T(P) + F(N)}$$

$$Specificity = \frac{T(N)}{F(P) + T(N)}$$

$$Accuracy = \frac{T(P) + T(N)}{T(P) + F(N) + F(P) + T(N)}$$

4.3 Case study comparative analysis

We can build up that our Case Study achieves great exactness for the medical data classification. Hybrid Adaboost Algorithm together with KNN algorithm is utilized for medical data classification in our investigation strategy.

And furthermore we can set up this forecast precision result by contrasting different classifiers. Case Study classifier is contrasted with the Hybrid Adboost KNN along with Krill Herd Algorithm (KHA), existing Ant Colony Optimization (AOC) and Support Vector Mechanism (SVM) classifiers. The Comparison results are introduced in the Table 1.

Table 1. Case study comparative analysis of the proposed and existing method

Datasets	Proposed Method (KHA+HAKNN)			Existing Method (AOC+SVM)		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
Mammographic Mass data	95.86%	98.5%	96.5%	87.1%	89.3%	94.45%

Accuracy:

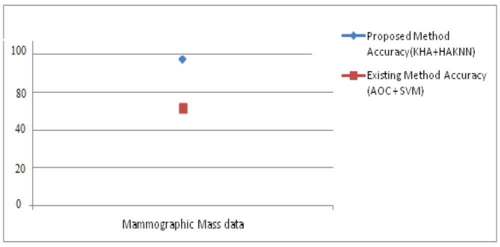

Figure 3. The comparison outcomes of the Accuracy measure

Sensitivity:

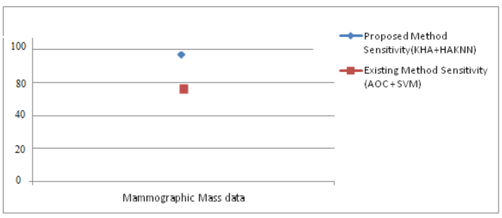

Figure 4. The comparison outcomes of the Sensitivity measure

Specificity:

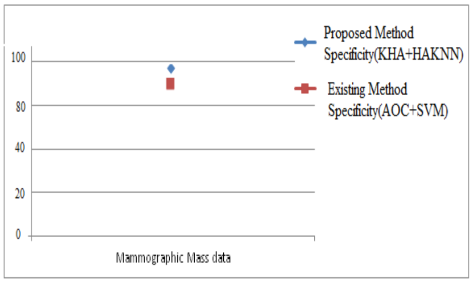

Figure 5. The comparison outcomes of the Specificity measure

4.4 Performance analysis

The results of case study assist in analyzing the effectiveness of the prediction method. The results of the breast cancer datasets are provided in below table 2

Table 2. Performance analysis of the proposed method

Dataset	Accuracy	Sensitivity	Specificity
Mammographic Mass data	95.86%	98.5%	96.5%

From Table 1, it is clear that the accuracy value for mammographic mass data obtained using the proposed method is 95.86 %, similarly the sensitivity and specificity value obtained is 98.5 % and 97.6 % respectively.

5. CONCLUSION

Breast cancer is danger disease among ladies around the world. Case Study investigation technique of Breast cancer data classification can be done with help of optimal feature selection. Krill Herd Algorithm (KHA) is used to selecting optimal features. The optimal features are classified with Hybrid Adaboost KNN classification algorithm. Experimentation data sets are collected from UCI machine learning public database. Case Study performance evaluated by utilizing accuracy, sensitivity and specificity. The Study investigation Hybrid Adaboost KNN technique achieve the maximum accuracy, sensitivity and specificity were 95.86 %, 98.5 % and 96.5 %. Case Study investigation implemented using python software.

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