

A K-Nearest Neighbor (KNN)-Algorithm in Poultry Diseases Monitoring System

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ABSTRACT

In poultry farming, the most important factor during their growth and production is for the birds to be free from any disease. Unmonitored and uncontrolled temperature and humidity within the cage can lead to reduced productivity and high rate of mortality. Diseases such as: avian influenza, Newcastle, fowl paralysis, semolina and so on may wipe up an entire farm in few minutes. This research used K- nearest neighbor (KNN) algorithm and developed a model to monitor such factors automatically. In the model, digital camera was deployed in the cage that records the behavior of the fowls. The model was trained on the normal behavior of a healthy/unhealthy fowl based on the clinical signs so that any abnormal sign reported immediately by the system. The experimental results show that the model can report the various diseases sign in poultry farms.

Keywords: LBP, CBN, Agriculture, Loan, Facial Recognition.

1.0 INTRODUCTION

1.1 Background of the Study

The best animal protein produced nowadays is chicken. Poultry chicken has a significant influence on our daily lives due to Nigeria's incredible food diversity. However, a number of serious illnesses regularly affect this sector. Infected bursal disease and other serpentine illnesses are more common, followed by nutritional deficiencies, colibacillosis, salmonellosis, Newcastle disease, chronic respiratory disorders, avian influenza, coccidiosis, aspergillosis, omphalitis, and fowl pox. Not only can machine learning help prevent and detect poultry diseases, but it can also be a useful tool in healthcare. Advanced computer science diseases that harm chickens include Newcastle disease and Avian Influenza. It is crucial to focus on poultry infection at its very early stage in order to avoid negative outcomes (Kader *et al.*, 2021). Artificial neural networks (ANNs) and support vector machines (SVMs) are potent machine learning approaches that have been used more and more for optimizing operating parameters, according to (Pazikadin *et al.*, 2020; Waqas *et al.*, 2022). These methods enable more effective and economical optimization procedures by providing a data-driven approach to modeling intricate interactions between input parameters and desired outcomes (Abbas, *et al.*, 2019).

ANN has clear benefits, especially for tasks that need to represent nonlinear relationships¹⁸. In applications like picture and speech recognition, ANN's ability to automatically identify complex patterns and features from unprocessed data eliminates the need for manual feature extraction (Guillod *et al.*, 2020). Because SVM performs well in high-dimensional spaces, it can be applied to applications involving a variety of

characteristics, such as picture recognition or text classification (Chandra and Bedi, 2021). SVM ensures the generalization of unknown data because it is resilient enough to overfit, especially when the number of features exceeds the number of samples. Their adaptability to different data distributions and flexibility in capturing complex decision boundaries are made possible by the variety of their kernel functions (Mohammadi *et al.*, 2021).

Utilizing ANN and SVM to optimize operational parameters for RHA to bio-oil conversion offers a data-driven and effective method (Waqas *et al.*, 2024). According to Nhu *et al.* (2020), these models support continuous efforts to improve the sustainability and efficiency of bioenergy production processes. Predicting the impact of the operating parameters still presents a challenge when choosing the right machine learning technique. This is because developing a model requires a significant amount of precise data. In order to forecast the production of bio-oil under the combined effects of temperature, heating rate, and particle size—a parameter that was not previously addressed by ANN and SVM—the current research contrasts machine learning and statistical techniques. One of the most important sectors of the world economy is the poultry business. It gives humans wealthy protein and nutrition, which promotes socioeconomic growth (Serbessa *et al.*, 2023). The growth of agriculture is the cornerstone of a nation's economic advancement. A significant portion of the meat and eggs generated by the chicken business are consumed by humans (He *et al.*, 2022). Global wealth and population expansion drive food demand, which drives greater chicken production in many countries. It is projected that there will be 8.6 billion people on the planet by 2030, which will make it extremely

difficult to produce and consume enough meat (OECD/FAO 2021). By 2050, demand for chicken meat and eggs is predicted to rise by 40% (Astill *et al.*, 2020).

Because poultry products are an affordable and valuable source of protein for a person's daily diet, poultry meat and eggs are vital to human life. For many rural farmers, raising poultry is a direct source of income for their family. For many different types of households, the small-scale chicken feeding sector provides a stable source of family income and employment because of its modest size and minimal investment requirements (Abayneh *et al.*, 2023). In order to accomplish sustainable development goals, it is essential to maintain sustainable food production and livelihoods at many scales. The growing demand for poultry is a significant opportunity for the sector, yet there are also ongoing difficulties. Human health and animal protein concerns have grown and are being given more attention as challenges from climate change, land erosion, biodiversity loss, and biosecurity increase. Long-term environmental changes are giving rise to new pressures, demands, and challenges (Pearson, *et al.*, 2022). Numerous illnesses, such as avian influenza, Salmonellosis, chicken cholera, Newcastle, and coccidiosis, can affect the poultry agricultural sector (Sharopatova, 2020; Krammer and Schultz-Cherry, 2023; Adere and Mukaria, 2023; Gkolia, 2023; Kuria, 2023; Mossie and Wondie, 2023).

Numerous studies have been conducted on the use of data mining and machine learning techniques for disease identification in the chicken business. Zhuang *et al.* (2018) reported that seven features are examined in order to use machine learning approaches for the identification and evaluation of poultry diseases. after assessing different search strategies. The approach is suitable for learning from tiny samples and diagnosing illnesses because of its strong general capabilities. This study's sample SVM outperforms the other methods with a result rate of 98.46% by utilizing the POLY kernel's function. Using Quach *et al.* (2020) their study described a hybrid structure based on the words "SURF" and "K-means" as a factor in the development of multi-layer CNN neural networks. merely a few facts sources It helps prevent undesirable risks like gradients that overcome and disappear. The model's operation, which categorizes more label types and uses in the poultry industry, will continue to be improved through research.

Zhang *et al.* (2020) predicted a method that increases the rate of broiler breeding survival and automates the analysis and monitoring of broiler behavior. Recognition accuracy and background recognition. Neethirajan *et al.*, (2020) stimulate the expansion of modern animal farming using sensing technologies,

large-scale data, and machine learning (ML) described in their study how the A mixed structure on SURF with another term called K-means contributes to growth in multi-layer systems. In the real world of pandemics, constraints make it difficult for farm visits to reach veterinarians, nutritionists, producers, Barns, and feedstocks; an in-the-moment understanding of the task structure, consumption, and output of cattle is required. These insights, made possible by sensing technology, produce data that can be accessed remotely in order to save costs and boost performance to satisfy customer needs. We demonstrated the effectiveness of machine learning for creating predictive models for upgrading AIV active monitoring systems, as Walsh *et al.* had predicted.

The research by Borgonovo *et al.*, (2020) shows that the methods described here can be used to detect coccidia infections in intensive chicken farms early on. Applying it to animal husbandry would be beneficial as well. This approach is ideal for procedures and precise animal husbandry goals, and it could offer a day-and-night monitoring system for enhancing animal health by notifying a veterinarian as soon as an infection occurs. Walsh *et al.*, (2019) also state that predictions for large as well as fresh amounts of data can be made quickly once the models have been trained. For example, our model makes it simple to forecast the likelihood of insulating AIVs mode on varied farming sample graphical view of MA & PCR null the rate. Garcia *et al.* (2020) anticipated that we would find that pasturing mostly has focused on sheep 40% and animal, utilizing machine learning approaches in recent years 60% Classification is the most effective. However, this review revealed that pasturing has also focused on other animals. Monitoring their health has been a regular responsibility on enhancing poultry output in terms of chicken health. The major goal of the research is using ML Algorithms and implementing the techniques to precaution of emerging illness of poultry industry. The objectives of the research include very much helpful for the farm owners as well the whole poultry industry because every year over 40% of poultry chickens died due to some random diseases. Our research will make a huge impact on this big lose over the year. Increase Poultry commodity to the communities. Increase financing income to the farmers and to prevent harmful consequences, it is important to concentrate about poultry infection on our very initial stage.

2.0 METHODOLOGY

The system works based on the framework presented for Poultry Diseases Monitoring System Using K-Nearest Neighbor (KNN)-Algorithm (Murtala, *et al.*, 2024) images recorded by a digital camera, the camera serves as input mechanism and the data generated by the camera from the behavior of the fowls inside the cage feeding the algorithm as test data, now since the training data is stored i.e clinical sign of the fowls.

Considering the fact that K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique, is non-parametric that assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories. It stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm. It is also called a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset. KNN algorithm at the training phase just stores the dataset and when it gets new data,

and then it classifies that data into a category that is much similar to the new data.

The K-NN working can be explained on the basis of the below algorithm:

- **Step-1:** Select the number K of the neighbors
- **Step-2:** Calculate the Euclidean distance of **K number of neighbors**
- **Step-3:** Take the K nearest neighbors as per the calculated Euclidean distance.
- **Step-4:** Among these k neighbors, count the number of the data points in each category.
- **Step-5:** Assign the new data points to that category for which the number of the neighbor is maximum.
- **Step-6:** Display result

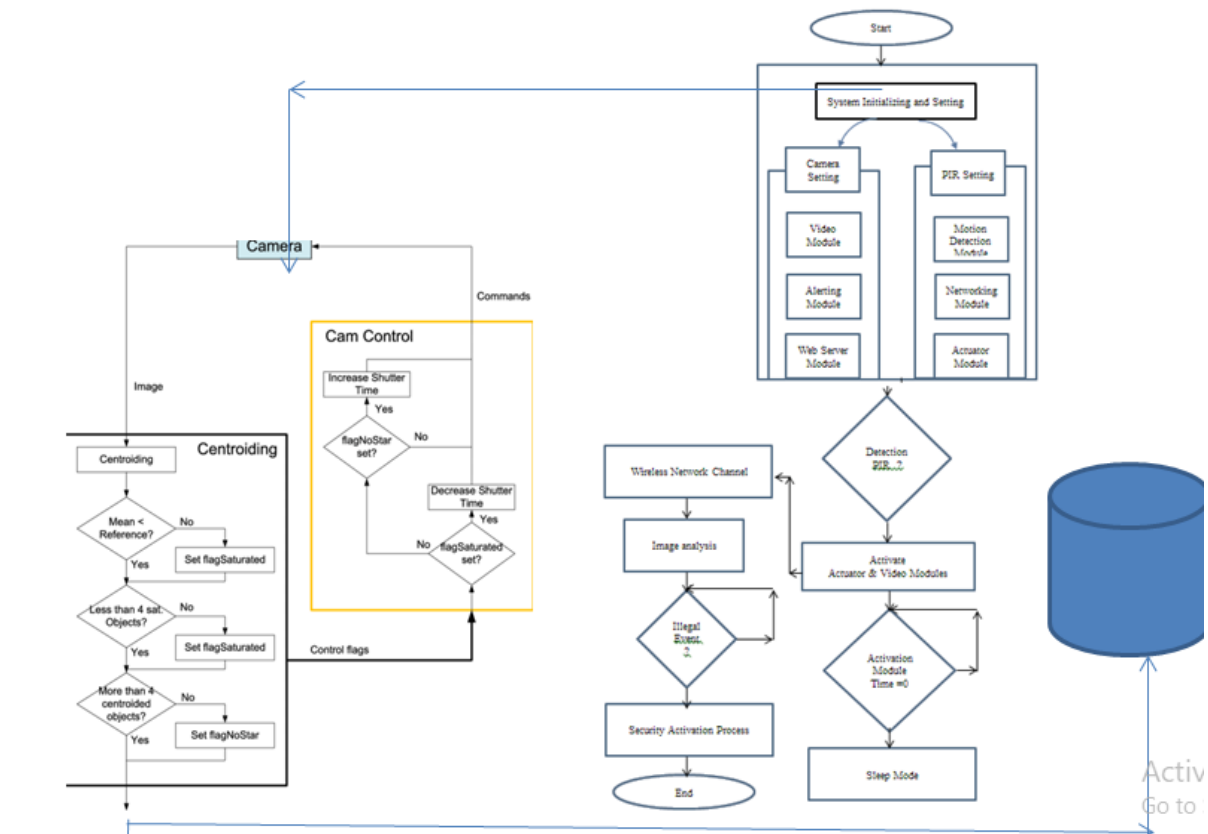


Figure 1: How the camera will be generating series of training images

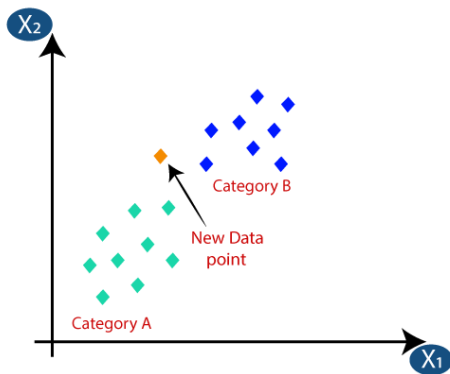


Figure 2. The classification process

Fitting K-NN classifier to the Training data

Now we fit the K-NN classifier to the training data. To do this we import the `KNeighborsClassifier` class of `Sklearn Neighbors` library. After importing the class, we will create the **Classifier** object of the class. The Parameter of this class are:

- **n_neighbors**: To define the required neighbors of the algorithm. Usually, it takes 5.
- **metric='minkowski'**: This is the default parameter and it decides the distance between the points.

- **p=2**: It is equivalent to the standard Euclidean metric.

$$d(x, y) = \left(\sum_{i=1}^n |x_i - y_i|^c \right)^{\frac{1}{c}}$$

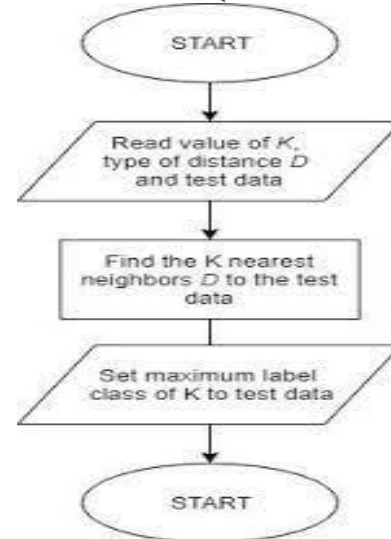


Figure 3. The summary of the entire system.

Method of operation

The system requests for an algorithms K-Nearest Neighbor (KNN)-Algorithm. The algorithm used K-nearest neighbor (KNN) algorithm to monitor such factors automatically. Digital camera was deployed in the cage that records the behavior of the fowls.

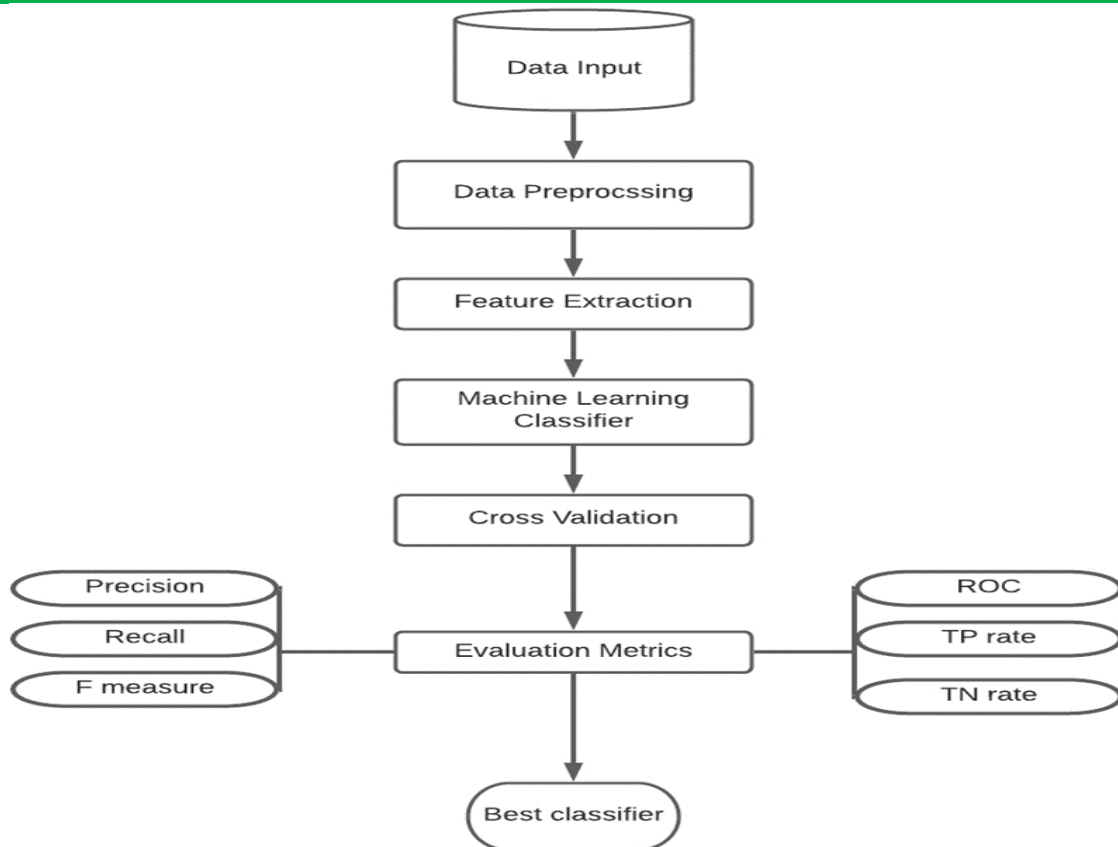


Figure. 4. Representation of Procedure of Poultry Disease Detection

Algorithms

The algorithms used are Algorithms 1, 2, and 3. Algorithm 1 is *Nrmlz* used to normalized images captured. It is used to normalize the images captured from digital camera and store them in a file called image file which will be used by the *KNN* model, this will make the images have the same size, shape and

intensity. Normalizing data before training a convolutional neural network (*KNN*) has many benefits, including increased accuracy and faster training times. Normalization helps to reduce the dominance of one feature over the others, which can lead to better generalization performance.

Algorithm 1

Begin

Function Nrmlz(int nmin, int nmax)

```

int d;
float factor;
byte r ← 0, g ← 0, b ← 0;
int *min ← &(m_image.minmax.min);
int *max ← &(m_image.minmax.max);
if (*max - *min = 0)
  factor ← 32767;
else
  factor ← (float)((float)(nmax - nmin)
int *p ← (int *) m_image.GetBits();
unsigned long n ← GetImageSize();
switch (m_image.ptype) {
  case GREY:
    for ( ; n > 0; n--, p++)
      Begin
        r ← RED(*p);
        d ← (int)((float)(r - *min) * factor + nmin + 0.5);
        r ← (byte)THRESH(d);
        *p ← BGR(r, r, r);
      end
  case cRGB:
    for ( n > 0; n--, p++)
      Begin
        r ← RED(*p);

```

Algorithm 2 reads images stored in a file and perform classification based on the clinical signs of fowl disease. The input to the file is the directory name of the files.

Algorithm 2**Begin**

```
Function def getListOfFiles(dirName):
```

```
listOfFile ← os.listdir(dirName)
```

```
allFiles ← list()
```

```
  for entry in listOfFile:
```

```
    Begin
```

```
      fullPath ← os.path.join(dirName, entry)
```

```
      if os.path.isdir(fullPath):
```

```
        allFiles = allFiles + getListOfFiles(fullPath)
```

```
      else:
```

```
        allFiles.append(fullPath)
```

```
      return allFiles
```

```
    end
```

```
imagePaths ← getListOfFiles("./datasets/")
```

```
data ← []
```

```
lables ← []
```

```
for image in imagePaths:
```

```
  Begin
```

```
    lable ← os.path.splitext(os.path.splitext(image)[0])[1]
```

```
    lables.append(lable)
```

```
    img ← cv2.imread(image)
```

```
    img ← cv2.resize(img, (32, 32), interpolation = cv2.INTER_AREA)
```

```
    data.append(img)
```

```
    data ← np.array(data)
```

```
    lables ← np.array(lables)
```

```
    le ← LabelEncoder()
```

```
    lables ← le.fit_transform(lables)
```

```
    myset ← set(lables)
```

```
    print(myset)
```

```
    dataset_size ← data.shape[0]
```

```
    data ← data.reshape(dataset_size,-1)
```

```
    display(data.shape)
```

```
    display(lables.shape)
```

```
    display(dataset_size)
```

```
    (trainX, testX, trainY, testY ) ← train_test_split(data, lables, test_size= 0.25, random_state=42)
```

```
    model ← KNeighborsClassifier(n_neighbors=3, n_jobs=-1)
```

```
    model.fit(trainX, trainY)
```

```
    display(classification_report(testY, model.predict(testX), target_names=le.classes_))
```

```
  end
```

```
end
```

Algorithm 3**Begin**

```
Function def KnnClassificationPlot(trainX, testX, trainY, testY):
```

```
  X ← meas(:,3:4);
```

```
  Y ← species;
```

```
  Xnew ← [min(X);mean(X);max(X)];
```

```
  k ← 5;
```

```
  metric ← 'euclidean';
```

```
  mdl ← kNNNeighbors(k,metric);
```

```
  mdl ← mdl.fit(X,Y);
```

```
  [distances,indices] ← mdl.find(Xnew);
```

```
  plot(X(1:50,1),X(1:50,2),'o');
```

```
  plot(X(51:100,1),X(51:100,2),'o');
```

```
  plot(X(101:150,1),X(101:150,2),'o');
```

```
  plot(Xnew(:,1),Xnew(:,2),'xk');
```

```
  theta = linspace(0,2*pi);
```

```
  for i ← 1:3
```

```
    x ← distances(k,i)*cos(theta) + Xnew(i,1);
```

```
    y ← distances(k,i)*sin(theta) + Xnew(i,2);
```

```
    plot(x,y,'-k')
```

```
  end
```

```
  function obj ← kNNNeighbors(k,metric)
```

```
    if nargin > 0
```

```
      obj.k ← k;
```

```
    end
```

```
    if nargin > 1
```

```
      obj.metric ← metric;
```

```
    end
```

```
  end
```

```
  function obj ← fit(obj,X,Y)
```

```
    obj.X ← X;
```

```
    [obj.name_labels,~,obj.Y] ← unique(Y);
```

```
  end
```

```
  function [distances,indices] ← find(obj,Xnew)
```

```
    distances ← pdist2(obj.X,Xnew,obj.metric);
```

```
    [distances,indices] ← sort(distances);
```

```
    distances ← distances(1:obj.k,:);
```

```
    indices = indices(1:obj.k,:);
```

```
  end
```

```
  function Ypred ← predict(obj,Xnew)
```

```
    [~,indices] ← find(obj,Xnew);
```

```
    Ynearest ← obj.Y(indices);
```

```
    dim ← 2 - (obj.k > 1);
```

```
    Ypred ← obj.name_labels(mode(Ynearest,dim));
```

```
  end
```

```
end
```

3.0 RESULTS

After implementing the above algorithms, some of the sample outputs are shown in Fig. 1 and Fig 2. Fig. 1 displays the clinical sign of various classes, while Fig. 2 displays result of the KNN classification.

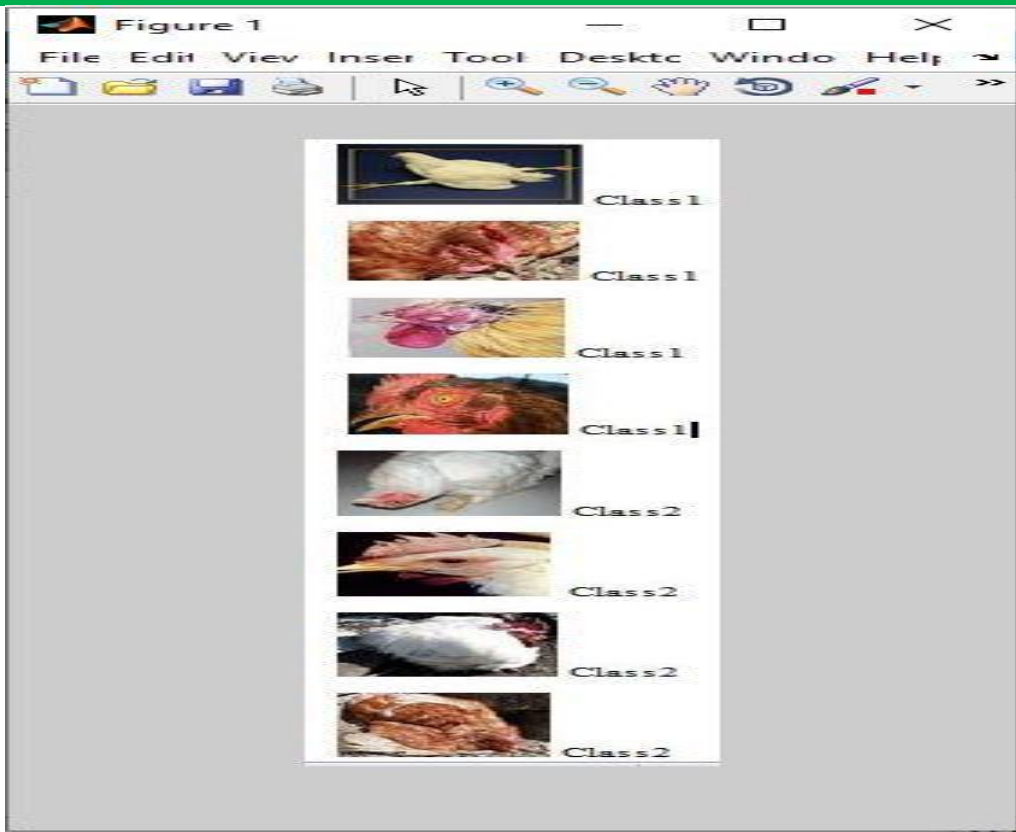


Figure1: showing the clinical sign

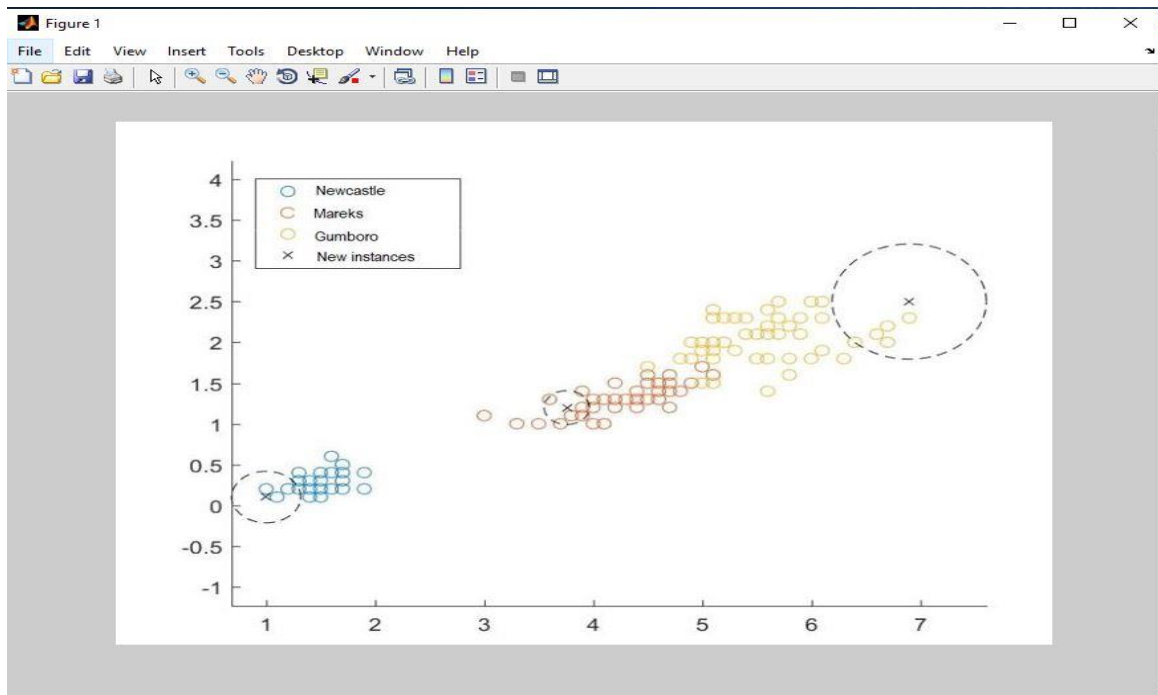


Figure 2: Result of the KNN classification

4.0 DISCUSSION

In this study, we outlined the shortcomings of previous studies; recognize the importance of KNN and Google edge algorithms in so many aspects of real life activities. A model was presented based on KNN algorithms to monitor diseases such as avian influenza, Newcastle, fowl paralysis, semolina and so on automatically that may wipe up an entire farm in few minutes. A digital camera was deployed in the cage to records the behavior of the fowls. The model was trained on the normal behavior of a healthy/unhealthy fowl based on the clinical signs so that any abnormal sign will be reported immediately by the system.

To assess the robustness of the model, experiments were conducted. The results show that this model can monitor diseases in farms especially poultry farm like AFMAH Integrated Farms in Damba Gusau, Zamfara State. Our proposed model is expected to be integrated with practical poultry farms, in AFMAH Integrated Farms in Damba Gusau, Zamfara State and thus to contribute to the poultry farms.

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