Original Article

Prediction Of Clinical Mastitis In Dairy Cows Using ANN

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Abstract

The ability of veterinarians to diagnose dairy cow diseases quickly and effectively is critical in dairy herd management. Electronic medical records have been utilised extensively to support clinical decisions for people utilising deep learning (DL). But veterinary diagnostics rarely use this technique. Furthermore, large datasets fuel most deep learning algorithms, disregarding the subjective knowledge acquired by veterinarians that is essential for illness diagnosis. This research suggests a DL approach for diagnosing dairy cow disease in order to address these problems: Artificial Neural Network (ANN). The model is trained using a dataset with parameters like Cow ID, Front Left Udder Inhale Limit, Day, Months after having given birth, breed, Front Left Udder Exhale Limit (IUFL), past incident of mastitis, Front Right Udder Exhale Limit(EUFR), Rear Left Udder Exhale Limit, Rear Right Udder Inhale Limit, Rear Right Udder Exhale Limit, cow temperature, udder hardness from manual intervention via switch, Front Right Udder Inhale Limit (IUFR), and pain from udder bloating. Mastitis cows are designated as 1, whereas normal cows are designated as 0. Experiments on dairy cow clinical datasets were carried out to validate its performance. The result show that our model performed well in disease diagnosis, with an accuracy rating of 99.090%, precision score of 99.100%, recall score of 99.100% and F1- score of 99%.The findings of the study have a significant impact on the fruitful, quick, and automated medical detection of illnesses in dairy cows.

Keywords: Artificial Neural Network, Deep Learning, Dairy Cow, Disease Diagnosis, Machine Learning.

Introduction

Early malady detection and treatment in lactating cows are essential in animal husbandry. The healthiness of dairy cattle is improved by early diagnosis and therapy that enables concentrated application as soon as is practical.

Mastitis or the mammary gland is inflamed by udder mastitis, which is one of the most prevalent diseases that results in financial losses since it reduces milk supply and results in animal deaths and earlier culling [1]. One or more udder quarters may be impacted by mastitis, which(mastitis) is broken down into two types: subclinical mastitis and clinical mastitis, the latter of which manifests symptoms. Clinical mastitis infections of the mammary gland are those that have visible symptoms such as hardness, pain, abdominal swelling, or redness. On the other hand, subclinical mastitis infection of the mammary gland does not result in any obvious changes in milk, udder, or rough appearance, making it challenging to find and treat. In such a case, the milk is tested in a laboratory to determine the diagnosis. Another way to classify mastitis is by the duration of the disease, which is referred to as acute or chronic mastitis. A timely diagnosis of clinical mastitis using highly precise, rapid techniques can help to maintain stock health while also reducing quantitative and qualitative milk production losses[3][4].

The diagnosis of disease in dairy cows is fairly comparable to that in humans. However, because animals cannot express their emotions verbally, the initial diagnosis is fairly difficult. The development of mastitis detection technology, sanitary conditions in the herd, animal genetics are being put to use to promote mastitis resilience, and other techniques are now accessible to dairy cows to assist them attain and perpetuate a healthy udder medical issue. The best techniques for detecting intra-mammary infections in cows are bacterial analysis and PCR assay. These techniques are costly and time-consuming, thus they cannot be used for normal population-level data collection [5][6]. Machine learning (ML) has proven to be effective at diagnosing human diseases as of late. The disease screening model based on clinical medical information is gaining importance in initial diagnosis. Maini et al. [5] used 5 Machine Learning (ML) techniques, including k-nearest neighbours (KNN), Logistic Regression (LR), Random Forest (RF), Naïve Bayes (NB), and Adaptive Boosting (AdaBoost), leveraging South Indian medical information to anticipate early cardiovascular diseases. Zhao et al. [F] used an RF model to predict chronic renal disorders. These techniques have been shown to be effective however they rely on manually extracted features to function properly. Deep learning (DL) has become more prevalent recently for use in malady diagnosis. In order to determine if a patient may develop Alzheimer's disease, Ljubic et al. [8] combined recurrent neural networks (RNN) and Long short-term memory (LSTM) to construct a DL model. To be able to forecast healthcare trajectories from medical records, Pham et al. [G] developed an LSTM model. These DL approaches work well for illness diagnosis since they automatically extract features from large amounts of labelled data. Unfortunately, the professionals' lack of diagnosis knowledge prevents the DL approaches from successfully uncovering the unrecorded relationships between diseases and symptoms. [7][9].

In this project, we have used deep learning more precisely Artificial Neural Network (ANN) for predicting the presence or absence of clinical mastitis disease in cows/cattle based on the class attribute present in the dataset. Mastitis cows are designated as 1, whereas normal cows are designated as 0. To determine whether dairy cows will develop clinical mastitis, the ANN-based model bases its prediction on the class attribute value [10][11][12].

Literature Review

Watban et al. developed and validated the Local Mastitis Test Reagent (LMTR) for the detection of Sub-Clinical Mastitis in domesticated creatures [13][14].

In this work, a cheap local mastitis test substance was created with the goal of detecting Sub-Clinical Mastitis (SCM), and its exactness, validity and efficacy were evaluated in the field. Using the DRAMINSKI Mastitis Detector, the electrical conductivity test and the California mastitis test were compared, and it was discovered that the LMTR had high level of reliability for SCM diagnosis than in the California mastitis test. The researchers suggest utilizing LMTR for the field examination of Sub-Clinical Mastitis because it is affordable and easy to prepare.

Tania et al. compare machine learning techniques to forecast dairy cows' udder overall health depending on somatic cell counts [15][16].

In order to foresee cows' udder health status based on somatic cell counts (somatic cell count at or below 200,000 cells/mL, a defined threshold), 8 distinct machine learning methods were compared in this study. These techniques included Random Forest, Linear Discriminant Analysis, Naive Bayes, Classification and Regression Trees, Generalized Linear Model with Logit Link Function, K-Nearest Neighbours, Neural Network and Support Vector Machines [17][18].

A Machine Learning Program to Predict Cow Mastitis Risk from AMS Sensor Data by Naeem et al.

To find the best criteria for determining threat of mastitis in cattle, supervised machine learning algorithms were used in this study. The application has a 98.1% accuracy rate, a 98.8% specificity rate, and a 99.4% sensitivity rate for predicting the danger of bovine mastitis based on the exhale and inhale limit of theanimals udders and the temperature of their bodies [19][20].

David et al. used neural networks to identify mastitis in dairy cows.This study set out to determine whether automatic milking cows with mastitis might be diagnosed and treated using neural networks (NN). 4,03,537 milkings from 478 cows were tallied in the data set. Udder therapy or mastitis diagnoses were made using somatic cell counts (SCC) over

1,00,000/ml[1], udder therapy, or SCC over 4,00,000/ml[2]. A NN model generated mastitis alerts using milk production rate, electrical conductivity, days in milk and milk flow rate as input parameters [21][22].

Dataset

The information is gathered from a cow's udder in order to identify clinical mastitis. The udder data is gathered using the four flex sensors, together with a temperature sensor. The milk quality property has two values: 0 for regular milk and 1 for abnormal milk. The model is trained using a dataset with parameters like Cow ID, Front Left Udder Inhale Limit, Day, Months after having given birth, breed, Front Left Udder Exhale Limit (IUFL), past incident of mastitis, Front Right Udder Exhale Limit(EUFR), Rear Left Udder Exhale Limit, Rear Right Udder Inhale Limit, Rear Right Udder Exhale Limit, cow temperature, udder hardness from manual intervention via switch, Front Right Udder Inhale Limit (IUFR), and pain from udder bloating. Mastitis cows are designated as 1, whereas normal cows are designated as 0. A faster way to track clinical mastitis in the cow is provided by analysing the data using an effective algorithm [23][24].

The dataset makes it possible for machine learning researchers with fresh ideas to dive immediately into a key technological field without having to collect or create new data sets, allowing for a comparison of the results to the effectiveness of prior work. The class attribute is used to gather information about both healthy and ill cows belonging to different classes. The data set is divided into two groups: a large group for deep neural network training and a smaller group for model evaluation. The test set is the last set that is used. On powerful GPUs, all models and training are carried out using the deep learning libraries Keras and TensorFlow. The declarative sparse categorical Binary cross-entropy function served as the loss function for all architectures that the Adam optimizer was applied to. We also employed ReLu activation functions in all layers, with the exception of the final dense layer where sigmoid is used. Source of dataset used here in the project is: [25][26].

https://data.mendeley.com/datasets/kbvcdw5b4m/1

Proposed Framework

The information is gathered from a cow's udder in order to identify clinical mastitis. The udder data is gathered using the four flex sensors, together with a temperature sensor. The milk quality property has two values: 0 for regular milk and 1 for abnormal milk. Cow ID, Front Left Udder Inhale Limit(IUFL), Day, Months after having given birth, breed, Front Left Udder Exhale Limit (EUFL), past incident of mastitis, Front Right Udder Exhale Limit(EUFR), Rear Left Udder Exhale Limit, Rear Right Udder Inhale Limit, Rear Right Udder Exhale Limit, cow temperature, udder hardness from manual intervention via switch, Front Right Udder Inhale Limit (IUFR), and udder bloating related pain are the data attributes. Mastitis cows are represented as 1, and there are two classes of normal cows represented as 0.

The ANN model is trained using the train set and then tested using the test set once the data has been divided into train set and test set.

In this study, we created a DANN from scratch: Deep learning enhanced supervised learning in general, deep learning methods for extracting picture and audio segmentation, and the learning capacity of features in highly dimensional unprocessed data.

A comprehensive grasp of deep learning algorithms thereby resolves the fundamental issue of sample selection and extraction, making it a suitable candidate for classification task modification. As a result, it exemplifies how simple functions can be combined with more complex features to provide a classification that is both sophisticated and effective.

Deep neural networks also feature a multilayer structure that prevents them from manually selecting time-consuming data qualities, which improves their ability to extract data properties. In this research, to forecast the clinical mastitis in dairy cows, we build and evaluate a small Deep Artificial Neural Network (DANN).

Artificial Neural Network (ANN) are designed using multi-layer, fully coupled neural network. They consist of an input layer, several hidden layers, and at last an output layer. There exists connections between every node in a layer and every node above it. The network becomes deeper as we incorporate more occluded levels.

It is essential that this framework is capable of learning and predict such interactions because many of the connections between inputs and outputs in real-life are both complex and non-linear.

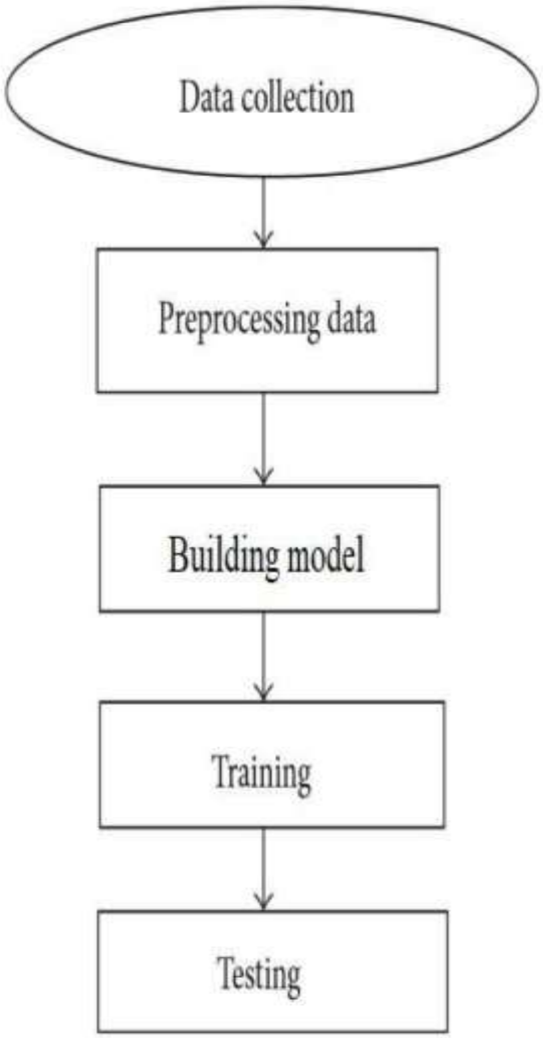

Fig: 1

Proposed FrameWork

Model Architecture:

- The ANN model we'll be utilising has seven levels: 1 input layer, 1 output layer, and 5 hidden layers.

- There are 11 units per neuron with ReLU as activation function in input layer's first layer.

- There are 11 hidden units or neurons with the ReLU activation function in the second, third, fourth, fifth, and sixth layers.
- • The output layer is the last layer and includes a single neuron with sigmoid activation, Adam optimizer and binary cross entropy loss.

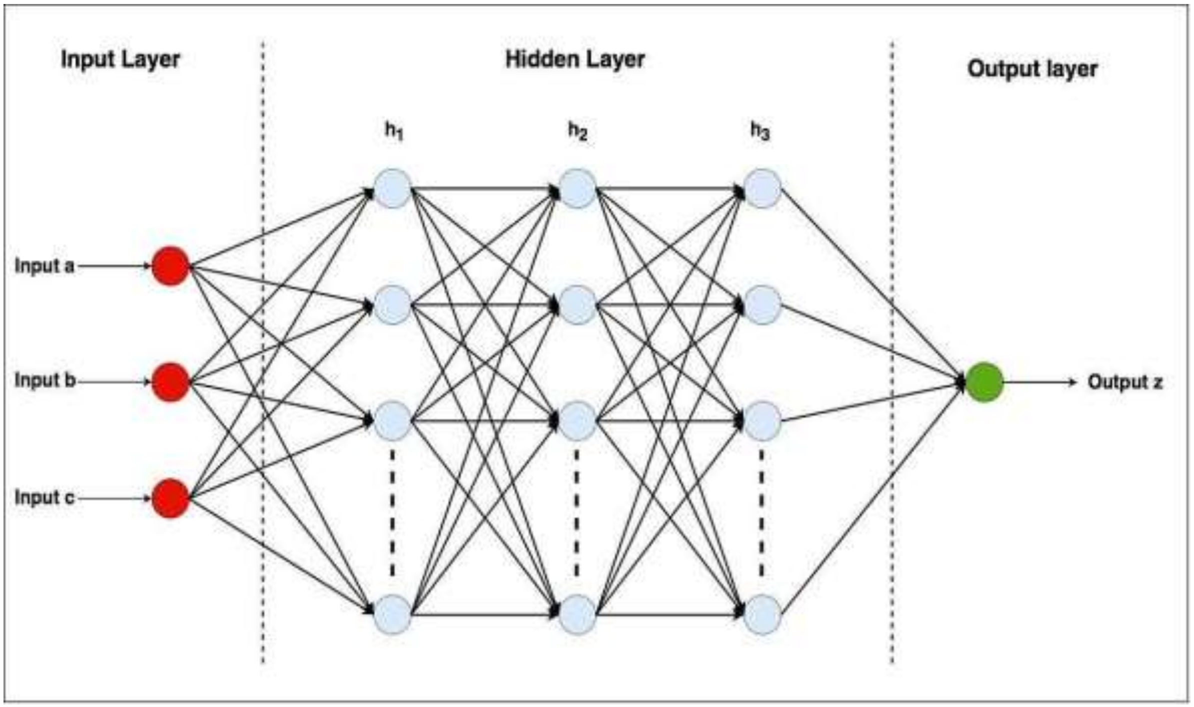

Fig : 2 **General ANN Architecture**

Result

True Positives (TP) are successfully anticipated high values, this implies that the worth of the anticipated and real classes is equal.

True Negatives (TN) are successfully anticipated negative values, it shows that the anticipated and actual class values are both negative. Consider the scenario where both the real class and the anticipated class state that the passenger did not survive.

False positive and false negative values happen when your actual class is different from anticipated class.

False Positives (FP) happen when the anticipated class is included but actual class is not. In this scenario, the predicted class would have told you that the passenger would live, but the actual class would have informed you that the person did not.

False negatives (FN) happen when the real class is present, but the anticipated class is absent. For instance, the passenger might be predicted to die, but their real class worth demonstrates that they lived.

Precision: By dividing the total no. of instances retrieved by right instances, precision gets calculated.

Precision: $P = \frac{(\text{True Positive})}{(\text{True Positive}+\text{False Positive})}$

Accuracy: Accuracy is 1 a deciding factor in rating classification models. An accuracy is the percentage of forecasts that our model was able to accurately anticipate. The official definition of is as follows:

Accuracy = $\frac{(\text{True Positive}+\text{True Negative})}{(\text{False Positive}+\text{True Negative}+\text{True Positive}+\text{False Negative})}$

Recall: Recall is ratio of correctly retrieved instances to totally number of successfully retrieved instances.

Recall: $R = \frac{\text{True Positive}}{(\text{False Negative}+\text{True Positive})}$

F_1-Score: F1- Score is computed as the weighted average of Recall and Precision. So, false positives and false negatives are both considered when calculating this score.

F_1-Score = $\frac{2*(\text{Recall}*\text{Precision})}{(\text{Recall}+\text{Precision})}$

Specificity: Specificity can be defined as the ability of the model to predict a true negative of each possible category. It is sometimes referred to as the true negative rate in literature. To calculate it formally, use the equation below.

Specificity = $\frac{(\text{True Negative})}{(\text{True Negative}+\text{False Positive})}$

Sensitivity: In machine learning, sensitivity is the variable that is used to evaluate a model's ability to predict the true positives of each possible category.

Sensitivity = $\frac{(\text{True Positive})}{(\text{True Positive}+\text{False Negative})}$

Logistic Regression: Logistic regression is a powerful supervised classification method (LR). The chances that a new instance is part of a particular class can be ascertained with the aid of LR. The outcome, which is a probability, falls between zero and one. In order to use the LR as a binary classifier, a threshold that can tell apart between two classes must be set.

Accuracy score: 89.7727%

Precision: 90.0%

Recall: 89.8%

F1-Score: 89.6%

Confusion Matrix:

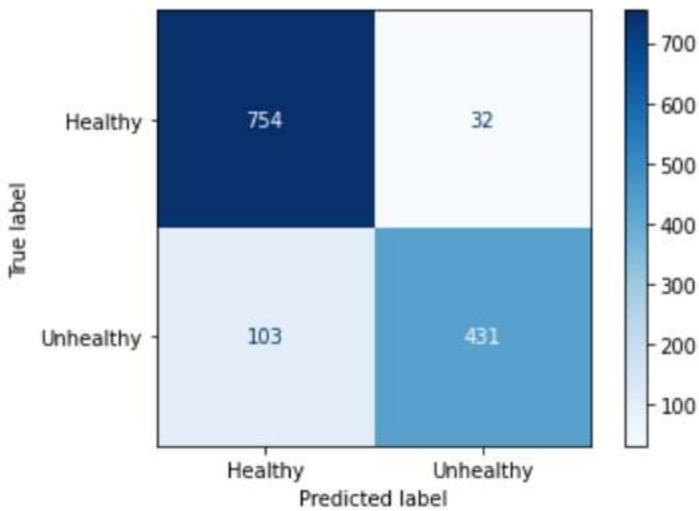

Fig: 3 (Confusion Matrix)

KNN:

The K-nearest neighbour (KNN) algorithm is one of the most primitive and straightforward classification methods. It is anticipated on the notion that the observations closest to a certain data point are the observations in a data collection that are the most comparable, and that we can therefore categorise unanticipated points depending on the value of the nearby existing points. To specify how many nearby observations will be used in the algorithm, the user can select K.

Accuracy score: 97.4242%
Precision : 97.4%
Recall : 97.4%
F1 – Score : 97.40%
Confusion Matrix:

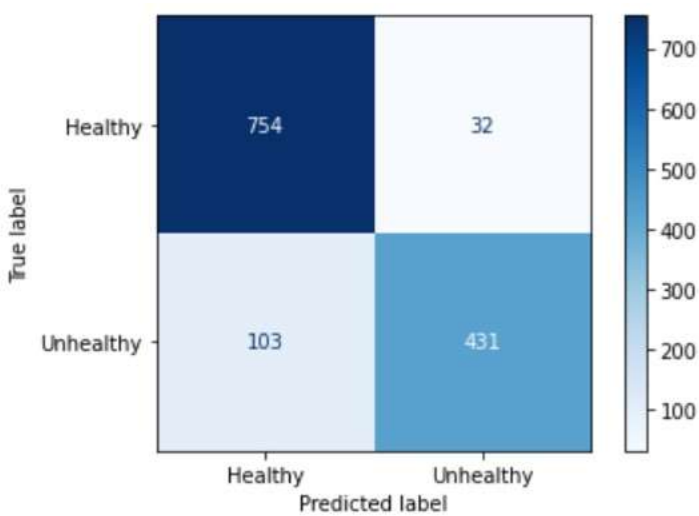

Fig:4 (Confusion Matrix)

SVM: The Support Vector Machine (SVM) technique is applicable to classify both linear and non-linear data. The first step is to map each piece of data into the n-dimensional feature space, where n corresponds to the total number of features. The next step is to locate the hyperplane that divides the data points into the two classes while maximising the marginal distance for each class and minimising misclassification.

Accuracy score: 90.5303%
Precision: 91.7%
Recall: 90.5%
F1-Score: 90.3%
Confusion Matrix:

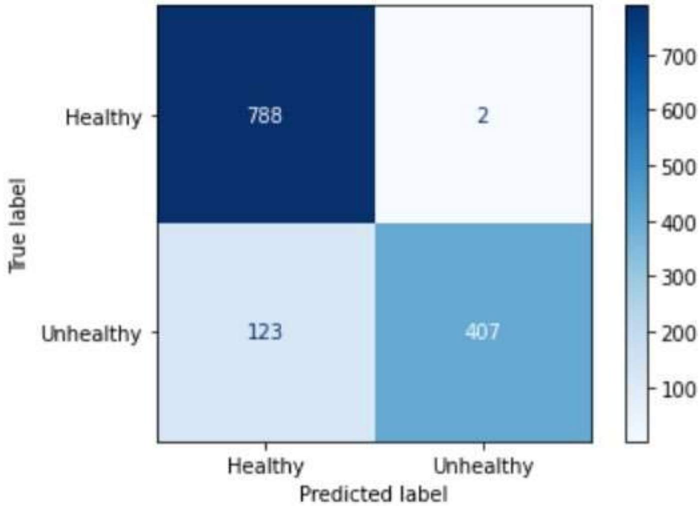

Fig: 5 (Confusion Matrix)

Deep learning:

11 neurons made up the input layer of the ANN model that we utilised, one neuron made up the output layer, and there were 6 hidden layers, each with 11 neurons.

Validation loss curve and loss curve:

The learning algorithm aims to obtain an appropriate fit, which can be obtained between an underfit and an overfit model.

A good match is when the training and validation loss both decrease to a stable point with only a small discrepancy between the two final loss values.

Nearly always, the training dataset's model loss will be lower than that of the validation dataset. As a result, the validation loss learning curve and the train learning curve are likely to differ. The "generalisation gap" is the name given to this discrepancy.

A learning curve map indicates adequate match if:

- At some point, training loss map flattens out.
- As it decreases to a steady point, there is a little difference between the validation loss plot and the training loss plot.

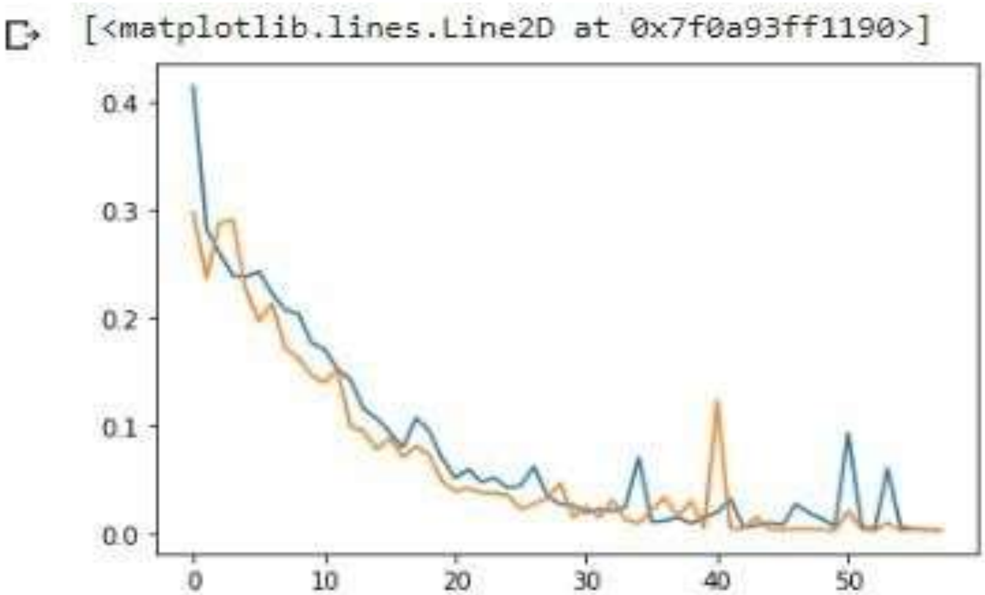

Fig: 6 (Loss Curve and Validation Loss Curve) This is a good fit.

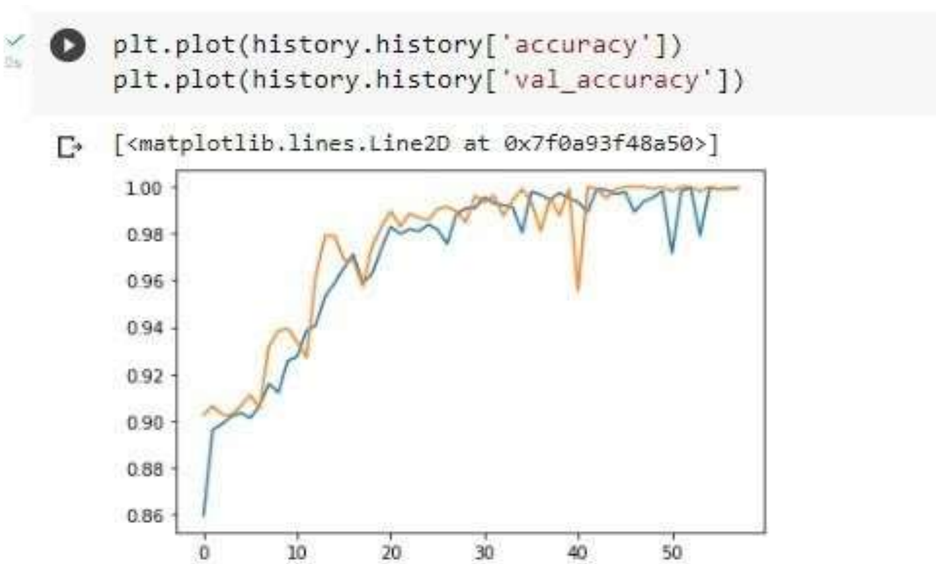

Fig: 7 (Accuracy and Validation Accuracy Curve)

The gap between accuracy and validation accuracy is less so our model is better classifier of clinical mastitis disease.

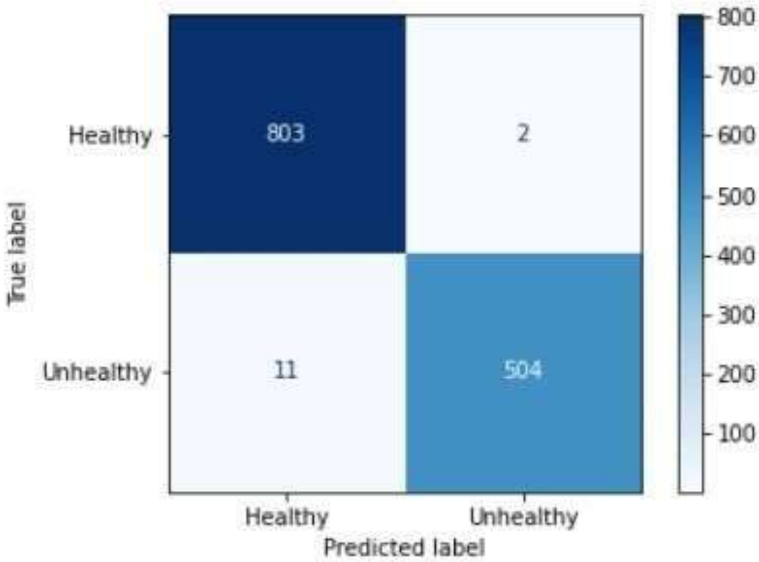

Fig: 8 (Confusion Matrix)

A N x N matrix known as a confusion matrix is used to assess the effectiveness of a classification model, where N corresponds to the total number of target classes. The anticipated goal values in the machine learning model are contrasted with the actual goal values in the matrix. Potent models have high rates of TN and TP and low rates of FP and FN.

The effectiveness of deep learning ANN model is described as follows:

The Clinical Mastitis dataset included a total of 6,600 samples. First, we divide the data set into an 8:2 ratio of 5280 training samples and 1320 testing samples. The training set was then further categorised as training and validation sets using an 8:2 ratio. Utilizing training data, the model is developed, tested using validation data and the using testing data, performance is evaluated. The suggested ANN model's effectiveness was assessed using the criteria of accuracy, recall, precision, f1-score, specificity, and sensitivity. We obtained 99.09% accuracy, 99.1% precision, 99.1% recall, 99.1% F1-score, 99% specificity, and 99.23% sensitivity after applying our suggested ANN model. This indicates that there should be a small but consistent discrepancy between the training and validation accuracy.

From above, we can draw the conclusion that the performance of our deep learning ANN model is much superior to the performances of other applied models (Logistic Regression model accuracy is 89.78, KNN model accuracy is 97.42 and SVM model accuracy is 90.53).

Conclusion and Future Work

By using CNN over the picture dataset, it is possible to further improve the prediction of clinical mastitis. We can build and evaluate a little deep convolutional neural network (DCNN) to forecast the clinical mastitis in dairy cows. The DL methods are effective for diagnosing illnesses since they automatically extract features from big amounts of labelled material. Deep neural networks also feature a multilayer structure that prevents them from manually selecting time-consuming data qualities, which improves their ability to extract data properties.

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