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An Optimal Texture Pattern Model of Big Data Processing for Canine Disease Classification

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Abstract: In the field of image processing, there are several varieties of data prediction models, each of which can identify the kind of data and determine how the data will be labelled. When compared to the other feature representation approaches, the texture pattern recognition method helps enhance prediction performance. As a result of the fact that this method of image texture feature extraction increases the amount of the features for the pictures, big data processing is achieved. In this study, an optimum image classification model for the canine image dataset was suggested to cope with the large amounts of data. During this process, the picture was analysed to determine the many skin diseases that canine slides had. Utilizing the Intensity Distributional Texture Pattern, we were able to successfully extract the texture pattern for the picture (IDTP). This represents the picture texture pattern by implementing the distribution function for the intensity of image matrix. As a result of this, the picture was categorized using the neural network model, and the performance of the suggested model was validated. The findings and the comparative analysis show that the performance of the suggested model is improved in comparison to the performance of the other conventional classification and prediction approaches.

Keywords: *Big Data Analysis, Big Data processing, Image Classification, Intensity Distributional Texture Pattern (IDTP), Neural Network (NN), Texture Feature Model.*

1. Introduction

THE image classification and prediction model incorporates many distinct structures for the validation and organization of image features and data. In this regard, the task of the prediction system is to identify the various classes of picture based on the qualities of those images and the training model. There are many different methods that are used in order to locate the similarities in the picture characteristics that reflect the categorization of various image kinds for each application. In more recent technological developments, Artificial Intelligence (AI) assists in making the prediction process operate as a more dependable capability of picture data categorization. because there are less contributions to be made in estimating the severity of the canine coccidiosis illness. This affliction is caused by parasites and manifests itself in the canine digestive system. Since this is a very little parasite consisting of a single cell, it may be identified using microscopic slides. In this regard, the classifications of illness are amenable to forecasting by the validation of picture characteristics at several important stages. When compared to other techniques of feature extraction, the representation of the picture that is based on the texture patterns helps to enhance the classification accuracy when used to this form of image classification. The methods of convolution are the ones that are most typically employed to locate the texture of a picture while trying to extract its texture. In order to extract the picture characteristics, the Discrete Wavelet Transformation (DWT) and Gabor convolution-based image texture prediction are used. Since some of the applications, such as facial image prediction and other object detection, follow binary patterns for the image matrix, such as Local Binary Pattern (LBP), Local Tetra Pattern (LTrP), Local Ternary Pattern (LTP), etc., some of these applications are known as "binary pattern applications." All of these are being done in order to zero in on the boundary difference in the picture matrix and locate the image's texture.

The attributes are organized into the vector format to represent the picture characteristics and any other pixel-related feature points after being extracted from the image using the model for image feature extraction. As a result of this, the choice of categorization is still another significant component that must be considered in order to accurately anticipate the kinds of images. Considering this, there are several machine learning strategies that can be utilized to categorize the image data. Some examples of these strategies include the Support Vector Machine (SVM) and the Fuzzy Classification Model, amongst others, and they can work with both binary and multi-class representations. Among them, the neural network method strengthens the data learning model and improves classification performance while maintaining a high sensitivity range. This was combined with the various domains of the image classification model, and it was verified with results that were superior to those of other conventional classification models. The accuracy of the prediction is improved when a

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neural network is used in conjunction with the process of picture texture extraction. As a result of the fact that the process of picture texture classification is plagued by issues such as too smoothed pixels, irrelevant similarity estimate, and insufficient proposer identification of similarity, amongst other issues,

The suggested work develops a multi-directional picture pattern representation for the precise recognition of surrounding pixels to get around these issues. The Intensity Distributional Texture Pattern (IDTP) based feature extraction approach may do this. In this IDTP, they were divided into blocks to locate the important pixels between its centre and its neighbours. The weight values of the cell were then computed from that magnitude. These are implemented across the whole picture matrix. The output matrix was then set up using this to represent the picture pattern. The feature vector of the picture was then computed using the histogram of the pattern. This was afterwards categorized by predicting the class label of canine coccidiosis illness kinds using the neural network model.

The main intension of this paper work can be listed as

1. By utilizing the IDTP's pattern extraction approach, the canine illness classification model is improved.

2. CGF filtering is used to minimize impulsive noise.

3. To cluster and analyse the filtered image by Enhanced pattern extraction method.

4. To extract textural and probabilistic features using multiple texture block with edge prediction based feature extraction methods.

5. The testing image's irregularity level will be classified using a boundary-mapped neural network-based classifier and texture.

The following sub-sections might be used to arrange the paper's overall details. Section II surveys the current systems for the classification model and the picture texture pattern extraction model. In section III, the suggested method and its stages are described together with an equation model for extracting picture texture and a classification model. The performance results of the suggested method with a comparative statement are confirmed and shown by statistical parameters in the graphical and tabular results in section IV. In Section V, the total project was wrapped up and justified. Additionally, the conclusion and the work's future scope were both stated.

2. Related Work

This study identifies the various texture pattern models and the picture category classification procedure for canine illness diagnosis. Additionally, this demonstrates the strengths and weaknesses of the current model of prediction system with various parameter representation and validation.

The publication [1] discusses how to anticipate Cystoisospora infection in Asian small-clawed otters in this passage. Additionally, it detects coccidial illness. This research identifies the DNA sequence representation and incorporates the morphological function for validating illness categories based on global structural patterns. Like this, the article [2] and [3] focused on how the Piroplasmoses illness was predicted to affect wild animals. The Bayesian classification approach is used to estimate the range of arthropod-borne illnesses in this instance. The Maximum Likelihood model for the oocyst DNA to identify the genetic pattern of the disease for animals was proposed by [4] in order to further increase the prediction level of the disease categories. The illness structure and specifics are verified and shown in [5] for the zoonotic parasite prediction. Because of this, there are classifications for parasite diseases. [6] provided a review of the Rhodococcus equip pVAPN type that causes pneumonia in dogs to validate the illness for canine species. In this, the data are organised using the Sanger method in a sequence form of representation in the form of forward and reverse vector feature mode. The automated system created this to enhance the data sequence model. According to the history, present, and future main aspects of data characteristics, the research [7] gave a review of canine theileriosis. The research [8] suggested a prediction of Babesia canis variability to distinguish the genotypes information of the animal data from the paralog’s information. In this, the validation procedure is accessed using the 18S rDNA and two mitochondrial markers. Like this, the report from [9] depicts a silver fox with adult-onset generalized demodicosis. Fluralaner can be used orally to treat this (Bravecto). Squamous cell carcinoma and avian papilloma are also examined in [10]. This essay discusses virological research that is histopathological and immunohistochemical in nature. Neospora caninum forms of intracellular parasite were considered in [11] for the diagnosis and prediction of illness species in dogs. Instead of using protein-30 encoding sequences, genome and transcriptome data were used to detect this. Making the patterns and variety of gastrointestinal parasites for red foxes in [12]. This depicts the animal's fine-scale diversity in urban surroundings. [13] analyses the species diversity and genome of harmful protozoa.

[14] examined K-means cluster analysis and here in big data a similar approach is used for Canine disease. In this case, Rickettsia rickettsii infection was used to assess the detection. As mentioned in [14] which uses Ant colony natures method and shortest path to establish the route, this paper addresses the concerns to use big data in shortest path. Like [15], canine intestinal parasite testing using faeces was conducted. Geographically, this was done in the United States, and the dog's visit to the vet was for that purpose.

The veterinary vaccinations were assessed in [16] and [17] using the centralized approval procedure of the European Union. This helped with the field research on veterinary vaccinations. Alginate Nanoparticles were used to estimate and improve the Anti-Clostridium perfringens in [18]. In this, illness kinds are predicted and analysed using pictures in the TEM format. For the morbidity in African lions, the feline immunodeficiency virus and coinfections have been discovered [19]. The multi-objective analysis of illness prediction begins with this kind of identification. The Stress-Related Herpesvirus Reactivation in Badgers was used to predict the kinds of Clostridium Proliferation [20]. The different illness kinds are categorized and recognised based on DNA structure. In [21], the Clinical Pathology data characteristics that are analyzed for the various illness categories included the Differential Diagnostics processing. In [22], Giardia duodenalis was anticipated and examined. This paper focused on the Rapid antigen testing, diagnostic real-time PCR, and faecal microbiota profiling.

3. Proposed Work

In this study, the multi-directional pixel representation approach was used to develop the texture-based canine picture categorization. To determine the difference between adjacent pixels based on the distribution model, the intensity distributional texture pattern (IDTP) was utilized. In this instance, the distribution is used to illustrate the similarity range for the boundary estimate in the image matrix. This raises the level of prediction based on the intensity variation of the cell matrix. The neural network and suggested texture pattern combination significantly increases the sensitivity of prediction performance.

The major goals of the suggested texture-based canine illness prediction are as follows:

1. The picture matrix's pixels are improved using the filtering method based on cellular automata.
2. The distribution-based with a high similarity value, this method of texture extraction calculates the depth information of the picture intensity.
3. Texture pattern extraction enhances the estimation of neighboring differences to represent the boundary.
4. This form of texture extraction estimates the depth information of image intensity with high similarity value.
5. With great precision and accuracy, the neural network-based system classes the feature matrix using the provided training data.

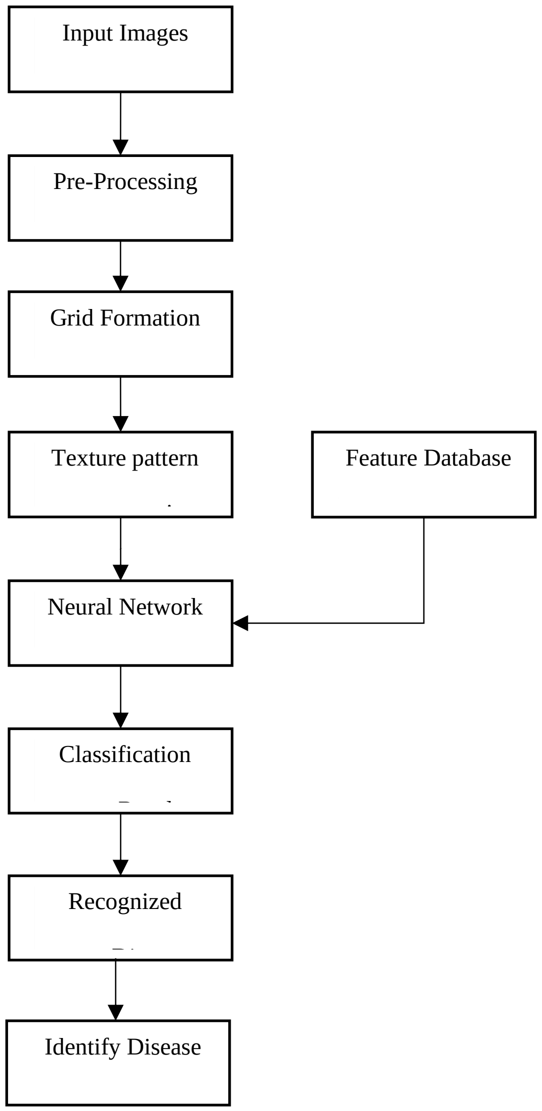

Fig 1 Overall flow diagram of proposed canine

The overall proposed model can be segmented into 3 sub-sections that are listed as,

a) Pre-processing,

b) Texture Pattern Extraction,

c) Feature Classifier.

3.1 Pre-processing

The picture was sent to the filtering model during this pre-processing stage, which enhances pixel intensity and smoothest out image pixels [21]. The filtering model's mask traverses the whole image matrix while performing convolution for each image cell and the mask value. This improves the pixels in the image. The term "cellular automata" refers to the application of the filtering and enhancing function to the picture through the cell generation of the image matrix. The border of the objects are improved using this filtering model's output using the depth information of the picture boundaries and other pixel attributes.

3.2 Texture Pattern Extraction (IDTP)

The representation of the magnitude difference between pixels and the normal distribution function based on probabilistic parameter estimate are used to create the IDTP-based texture pattern extraction. Figure 2 displays an overview block diagram of models for extracting texture patterns using binary matrices. The detailed steps of the proposed IDTP algorithm is explained in Algorithm 1.

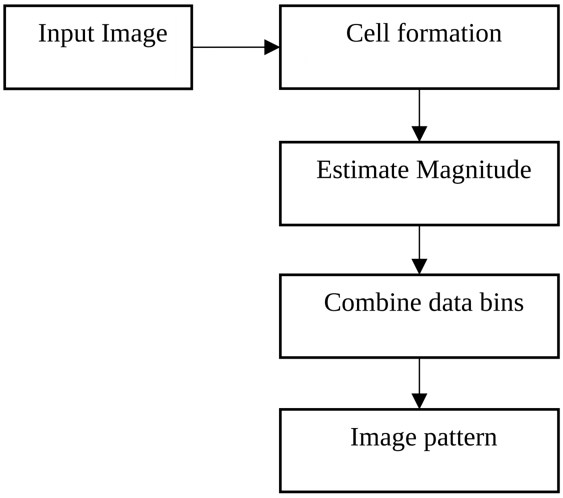

Fig 2 Block diagram of Texture Pattern

Figure 2 displays an overview block diagram of models for extracting texture patterns using binary matrices.

Algorithm 1: Texture pattern algorithm (IDTP)

Input: Image, I_M

Output: Texture pattern of the image, I_T

Initialize distribution parameter based on the filter coefficient of Gaussian.

Apply equation (1) to convolute the image matrix that is represented as 'G'.

Apply zero padding for the boundaries of image to fill the outer layer of image matrix.

Initialize I_V matrix to represent the mask of the image before projecting to the cell of image.

For i = 3 to p-2 **loop** // The loop 'i' for running mask over row of image from 3 to p-2

For j = 3 to q-2 **loop** // The loop 'j' for running mask over column of image from 3 to q-2

Let, $I_V = G(i-2: i+2, i-2: i+2)$

Let, $I_h = G(i,j)$ // Center pixel of cell, 'I_V'.

Initialize $b = 0$.

For k = 1 to length(I_V) **loop**

Estimate the neighboring combination 'α_k' from (5).

Calculate the mean difference 'μ_k' for 'k' iteration by (6).

Calculate the center pixel difference of the cell 'μ_c' from (7).

Find the sign change with the difference matric and arrange in the vector 'b'.

Convert the binary stream of data to decimal value and arrange it in the outer matrix as from (9).

End loop 'k'

$I_T(i-2, i-2) = b$

End loop 'y'

End loop 'x'

Let 'I_V' be the 5×5 matrix of the image cell that are to be convolute the image as 'G'. This can be represented as in equation (1).

$$G(i,j) = F(i,j,\sigma) * I_M(i,j) \quad (1)$$

Where, $F(i,j,\sigma)$ – Coefficient Gaussian distribution function.

Equation may be used to estimate the Gaussian Coefficient. (2).

$$F(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

Where, 'σ' represent the standard deviation of the distribution function. i and j are the spatial coordinates and indexes of the image matrix.

Convolution of the picture with the filter coefficient of the Gaussian distribution function may be used to estimate the gradient of the image matrix.

Let the magnitude $\left(|H_{ij}|\right)$ and gradient $\left(\alpha(i,j)\right)$ of the convoluted matrix are estimated by the equation (3).

$$|H_{ij}| = \sqrt{H_i^2 + H_j^2},\ \alpha(i,j) = \tan^{-1}\left(\frac{H_i}{H_j}\right) \quad (3)$$

Where, 'i' and 'j' are the cell size

$$H_i = \frac{\partial C_I}{\partial i} \text{ and } H_j = \frac{\partial C_I}{\partial j} \quad (4)$$

The gradients are extracted for the different directions of projections that are referred as $\{+90^0, +45^0, 0^0, -45^0, -90^0\}$.

The neighboring difference, 'α_k' from the image cell was estimated as in equation (5)

$\alpha_k = \{I_V(k-1:k+1, k-1:k+1)\}$ (5)

The mean value of the segmented mask can be represent as 'μ_k'. This it identifies the overall boundary pattern of the image. This can be calculated by (6).

$$\mu_k = \frac{1}{8}\sum_{a=1}^{8} \frac{|\alpha_k(a) - I_V(i,j)|}{I_V(i,j)} \quad (6)$$

Similarly, the center of the image cell matrix can be estimated by (7). This can be represented as 'μ_c'.

$$\mu_c = \frac{1}{8}\sum_{a=1}^{8} \frac{|\alpha_k(a) - I_h|}{I_h} \quad (7)$$

This all the combination of boundary and the center of matrix μ_k and μ_c are calculated for the overall image matrix. The magnitude that is near the edge of the objects is represented by the difference in picture pixel. This leads to an estimate that the sign difference represents the change in pixels at the border region. This can be represented as 'S' in (8).

$$S = \begin{cases} 1, & if(\mu_k > \mu_c) \\ 0, & Otherwise \end{cases} \quad (8)$$

From this stream of sign change estimation, the binary identification was represented and arranged it in the array of 'b' in (9).

$$b = b + (2^{k-1} \times S) \quad (9)$$

This binary formation was calculated for the overall image that are projected by the mask of convoluted image matrix.

For the slides impacted by the canine illness, this kind of pattern extraction model locates the picture border to indicate the depth of cell structure. The histogram was computed and expressed as the feature vector for the provided input picture based on the depth of the image's pixels. This distribution-based texture extraction technique improves the image matrix's feature representation. This was done using the canine image training and testing datasets.

3.3 Feature Classification

The sugested texture-based image classification model is used to carry out the recommended distribution-type feature representation and validation approach. The feature vector of the image matrix is made available for the training and testing of the prediction model based on the classifier. This proposed classification of canine disorders was validated using the Neural Network classification approach [22].

The classifier is essentially used for several classification models, such as binary and multi-label classification models. The grouping and organization of the features in that situation are reliant on the integration of relevant feature vectors. According to the relevant qualities, the features are trained to determine the range and construct rules based on similarity estimate. According to the matching point, the network in the NN is built to represent the training model of the NN.

In this study, the NN approach is used to assess the picture texture feature. Figure 3 depicts the classifier's architecture, which consists of a mixture of NN's neurons. The feature vector that is used as the classifier's input is represented by the letter "X" in this. The similarity prediction first structured this. From then, the network is created according to the relevant feature vector parameters and properties. The relevance between the feature characteristics is calculated and anticipated as the class label produced from the correlation of feature matrix

4. Result Analysis

This study analysed the Canine Coccidiosis picture dataset using the data prediction and classification model that was implemented (https://www.kaggle.com/kvinicki/canine-coccidiosis). In the python version of the programme, the overall model (3.8). The parameters of Precision, Recall, Kappa Coefficient, Accuracy, Sensitivity, Specificity, and F1-Scores were used to validate the suggested optimum

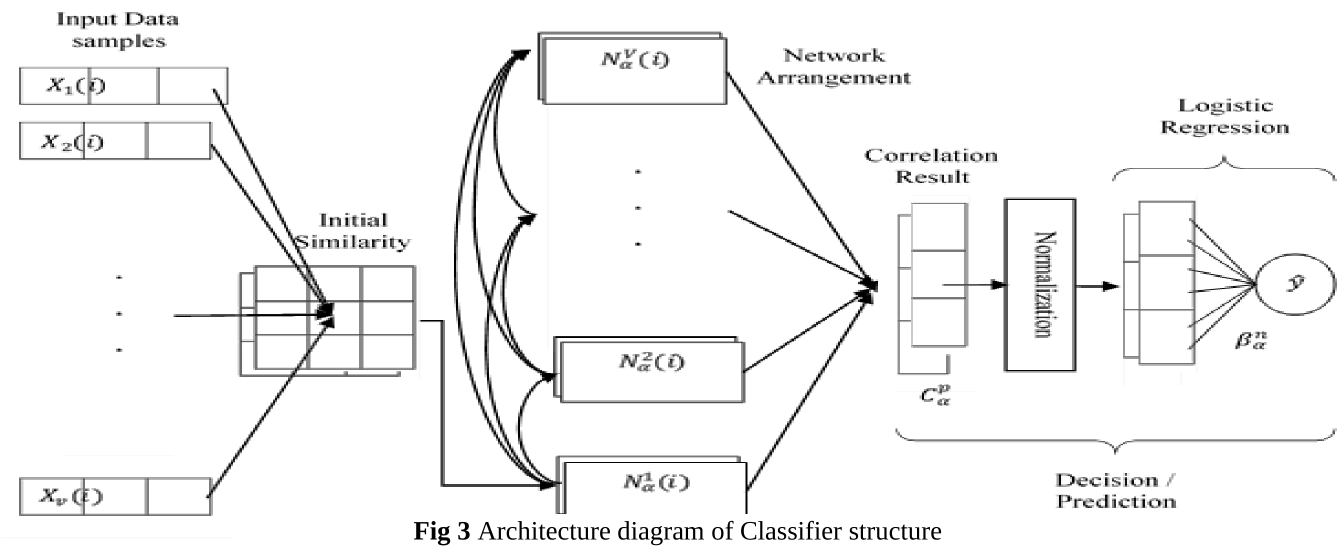

Fig 3 Architecture diagram of Classifier structure

feature classification model's performance. All of them are contrasted with the current Group Assignment techniques in [23]. The OVASSAY passive flotation (O-pf) and VETSCAN IMAGYST centrifugal flotation (VS-Icf) from [24].

Table 1 Precision and Recall of different classification methods

Methods	Precision (%)	Recall (%)
VS-Ic	71	70
O-pf	89	89
Xception	91	91
VGG	92	92
Densenet	93	93
Proposed	95	94

Table 2 Micro and Macro F1-Score

Methods	Macro F1-Score (%)	Micro F1-Score (%)	Macro Average F1-Score (%)
VS-Ic	70.43	70.67	76
O-pf	89.1	89.3	90
Xception	90.61	90.66	91
VGG	92	92	92
Densenet	93.35	93.33	94
Proposed	95.72	95.59	95.46

Table 1 displays the comparative results for the parameters of Precision and Recall in terms of suggested and other current approaches (percent). The sensitivity of the categorization model is represented by accuracy and recall. In comparison to other models, the suggested model succeeded in that by 95%. The Macro and Micro F1-Score measurements to confirm the precision of picture texture analysis are shown in Table 2.

The comparative bar charts of the accuracy with recall and F1-Score measurements from the current models cited in [23] are shown in Figures 4 and 5, respectively. In a similar vein, figure 6 displays a comparison of accuracy and kappa coefficient. The accuracy level is represented by both parameters, although in distinct ways. This is based on the outcomes of the observations and the dataset's ground truth. The comparative table for the sensitivity and specificity of canine illness image categorization is shown in Figure 7.

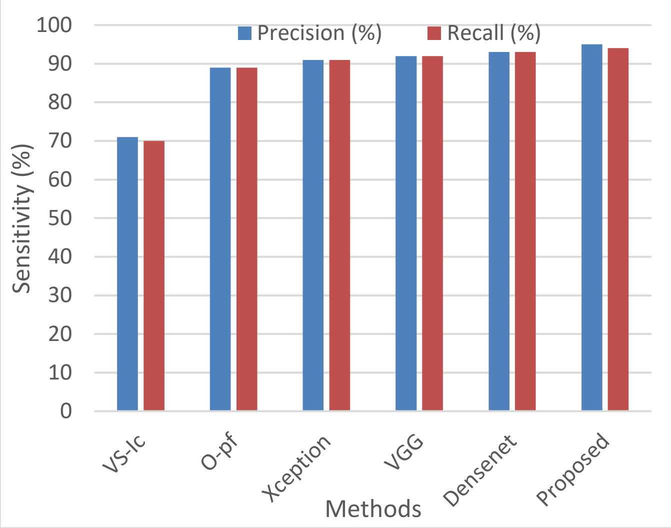

Fig 4 Sensitivity measures

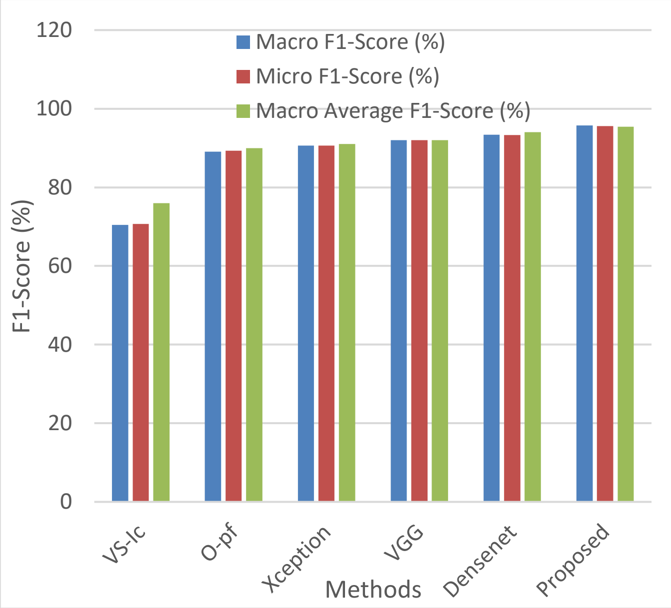

Fig 5 Comparison chart of Micro and Macro F1-Score

The comparison between accuracy and kappa-coefficient validation is shown in Table 3. The accuracy from this investigation was reported to be around 3% greater than the current model of picture categorization from [24].

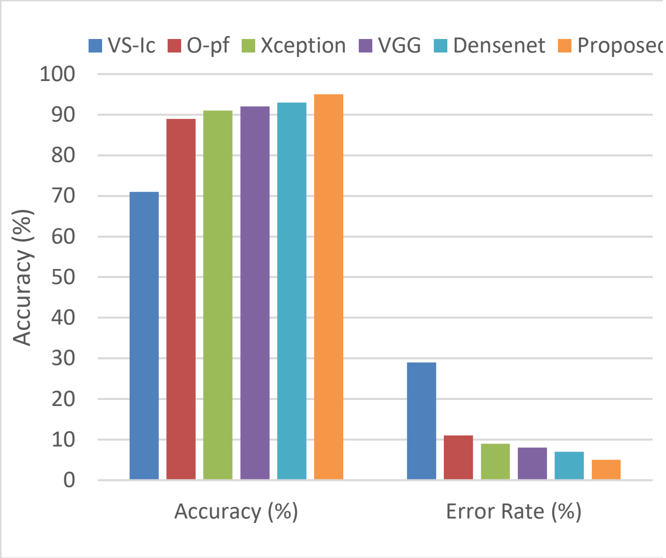

Fig 6 Comparison chart of Accuracy and Error Rate

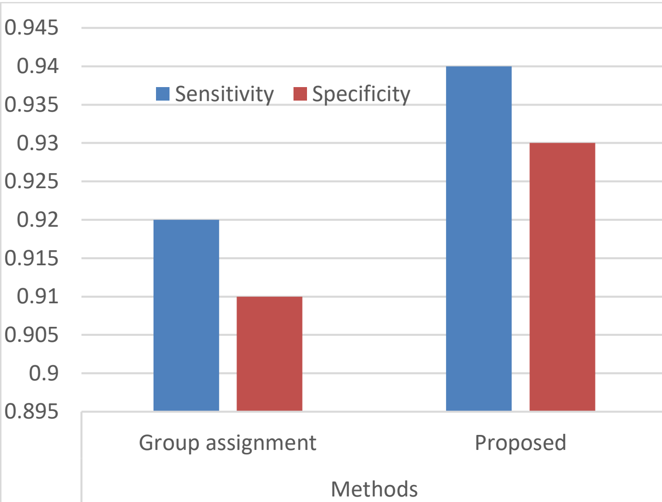

Fig 7 Sensitivity and Specificity comparison chart

The performance comparison of the proposed work to the group assignment model from [23] is shown in Tables 4, 5, and 6. Sensitivity, specificity, precision, F1-Score, Mathews Correlation Coefficient (MCC), accuracy, and Kappa Coefficient are the variables that are utilized for validation. For the accuracy validation, these are all shown as in the graphical chart in figures 8 and 9.

Table 3 Validation of Accuracy and Error Rate

Methods	Accuracy (%)	Error Rate (%)
VS-Ic	71	29
O-pf	89	11
Xception	91	9
VGG	92	8
Densenet	93	7
Proposed	95	5

Table 4 Comparison of Sensitivity and Specificity from [23]

Parameters	Methods	
	Group assignment	Proposed
Sensitivity	0.92	0.94
Specificity	0.91	0.93

Table 5 Comparison of Accuracy and Kappa Coefficient from [23]

Parameters	Methods	
	Group assignment	Proposed
Kappa Coeff	0.91	0.93
Accuracy	0.92	0.94

Table 6 Performance Evaluation from [23]

Parameters	Methods	
	Group assignment	Proposed
Precision	0.92	0.94
F1_Score	0.91	0.928
MCC	0.88	0.91

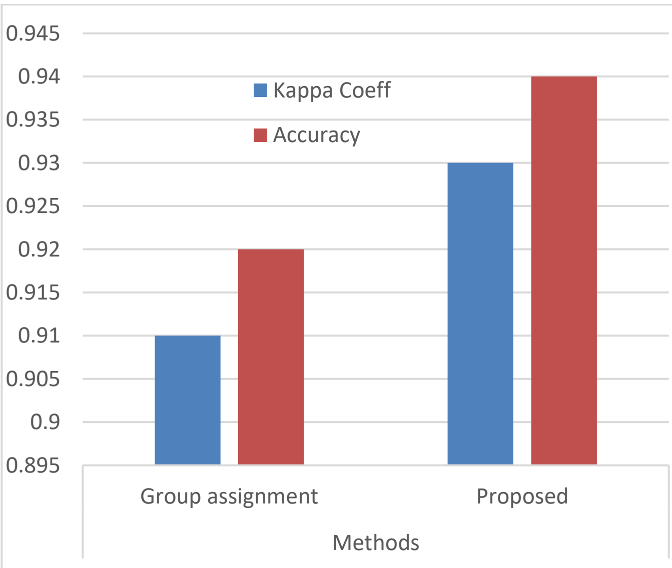

Fig 8 Accuracy comparison chart for proposed and [23]

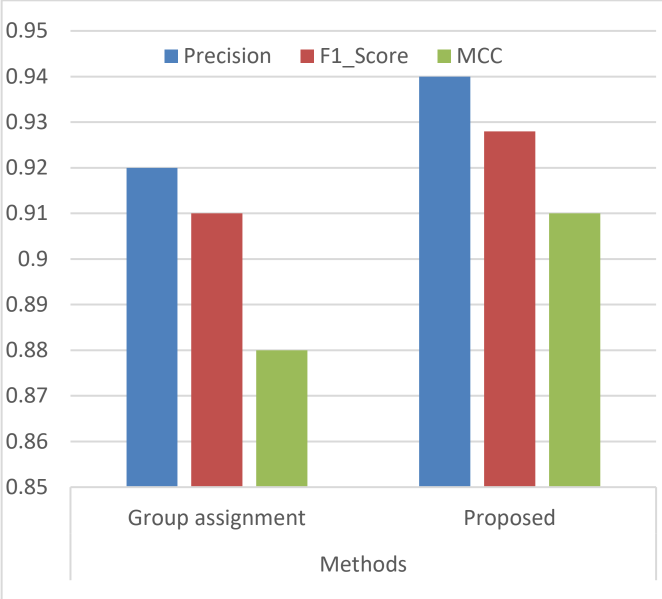

Fig 12 Performance Evaluation of proposed and [23]

The comparison outcomes and graphs demonstrate how well the proposed model classifies data and chooses the most effective texture extraction technique. These analyses have increased the recommended model's accuracy, and when compared to other state-of-the-art methods, it has a 95 percent overall sensitivity.

5. Conclusion and Future Enhancement

The large data processing for the picture dataset utilizing the best texture feature modelling was the main emphasis of this article. By decreasing the ideal size of feature data, this improves classification performance and processing speed. When compared to previous texture extraction techniques, the distribution-based image texture analysis enhanced the feature representation of the image. This was verified by comparing the outcomes with those of other current models utilizing the neural network classification approach [26]. This was supported by the outcome analysis, as the suggested model increased the performance of canine illness prediction and categorization by about 95% accuracy.

By predicting the image's gradients and multi-directional texture, this was improved upon in subsequent studies. By strengthening the prediction model for the large data processing structure, the classification performance was further enhanced.

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