Formulation of Pattern Recognition Framework - Analysis and Detection of Tyre Cracks Utilizing Integrated Texture Features and Ensemble Learning Methods

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Abstract. *For a safe drive with a vehicle and better tyre life, it is important to regularly monitor the tyre damages to diagnose its condition and chose appropriate solution. This paper proposes a framework based on pattern recognition utilizing the strength of texture attributes and ensemble learning to detect the damages on the tyre surfaces. In this paper, a concatenation of the statistical and edge response based texture features derived from Gray Level Co-occurrence Matrix and Local directional pattern are proposed to describe and represent the tyre surface characteristics and their variations due to any damages. The derived features are provided to train machine learning algorithms using ensemble learning methods for a better understanding to discriminate the tyre surfaces into normal or damaged. The experiments of tyre surface classification were conducted on the tyre surface images acquired from Kaggle tyre dataset. The results demonstrated the ability of the combined texture features and ensemble learning methods in effectively analysing the tyre surfaces and discriminate them with better performance provided by adaboost and histogram gradient boosting methods.*

Keywords

Ensemble learning, features, GLCM, LDP, texture, machine learning, tyre surface.

1. Introduction

Tyre is an integral part of a vehicle that keeps it moving establishing a continuous contact with the road surface. The tyre treads play a significant role in ascertaining the continuous contact and indicating the health of the vehicle. It facilitates smooth driving, protection against aquaplaning, brilliant snow and mud handling capabilities, excellent road holding grip, low rolling resistance and very good curve stability. The physical condition of the tyre depends upon various factors such as climate, road conditions, the driving style and frequency of use of the vehicle.

The tyres of the vehicles are affected by various parameters that include: force exerted on the tyre, velocity at which the tyre moves, geometry of the contact, type of the contact surface and environmental factors. Tyres in continuous use and contact with the road surface gradually wear down due the friction generated between them. This affects the depth of the tyre treads. Further tyres can be damaged due to various reasons that include: punctures, cracks, irregular wear, cuts, punctures and bulges. It is also important to observe the depth of the tread as the allowable limit is 1.6 mm above which the tyre has to be replaced. Damaged tyres lead to unsafe driving. Thus, regular monitoring of damages is much essential to diagnose its condition and chose appropriate solution.

Thus, maintenance of the tyre is important for a better tyre life and safe drive.

Traditionally the tyres are inspected manually for any damages and wear, additionally the tyre pressure is frequently tested as the improper distention can lead to uneven wear in tyre. And regularly wheel alignment and balancing has to be checked for maintaining even tyre wear. With the advancements in the technologies other methods/techniques were explored to identify the state of the tyre.

Sensor based methodologies were found to be promising in detecting wear in the tyre tread patterns. A RFID based tyre wear detection system was devised by [1]. The complete system was embedded in the tyre that provided warning if tyre wear is detected. A system based on laser sensors was developed by [2] for accurate identification of the tyre wear. Later as an improvement [3] discussed about tyre control system that incorporates sensing technologies with wireless data transmission into tyres to monitor pressure, wheel loading, deformation, wheel loading, tread wear and friction. However, the installation of sensors and data transmission modules into a tyre is quite challenging. Further modelling based methods were investigated to detect and analyse tyre wear. An analysis on the deformation of the tyre using the frictional characteristics between road surface and tyre based on tyre brush model was carried out by [4] and [5]. Similarly, a computer based tyre tread wear predictive system was developed by [6] where the method also assessed the key parameters that affect the tread wear.

A study on Tyre Wear Quantity and Difference (TWD) was done by [7]. The study aimed at devising a mathematical model to analyse the effect of the vehicle speed, braking force, road feature and steering angle to evaluate the TWD during unsteady condition of the vehicle. Further the experimental results conveyed the significant effect of braking force, road surface and vehicle speed on TWD. [8] estimated the amount of lateral tyre wear devising a nonlinear dynamic model for multi axle steering vehicle. A comparison was also made between the linear and nonlinear models, of which nonlinear model proved to be better for tyre wear estimation. The nonlinear model proved to be significant in its use for design and optimization of various parameters of vehicle for reducing tyre wear. Finite Element Analysis was implemented by [9] to estimate the cross-sectional wear for a specific conditions of the vehicle. This methodology considered driving style, system of vehicle and tyre construction effects to predict the tread wear. A method based on abrasion model is presented in [10]. The model considers abrasion and directional effects to calculate the tyre tread wear.

The developments in computer vision, image processing algorithms and artificial intelligence technology is providing solutions based on automation to detect tyre degradation or defects. These frameworks are developed to detect the tyre defect automatically and provide appropriate action. A method using X-ray images was used in [11] where texture features derived from the images were evaluated for texture dissimilarity and then provided to the segmentation algorithm to identify the defects. An analysis of the method proved to be good in identifying the defects on both side walls and tread patterns. An investigation was carried out in [12] to understand the deployment of Deep learning methods to identify the tyre defects. The method used regularization techniques to enhance the performance. A tyre life prediction system is presented in [13] based on pattern recognition framework. The method used texture features to train k nearest neighbour classifier to predict the tyre wear and the system proved to be effective in predicting with better accuracy. A combination of supervised and unsupervised machine learning methods is implemented in [14] to identify the tyre defects and their classification. The method used Laser sensor and a camera where the data obtained from the Laser sensor was used to detect the defects using clustering algorithm and later the defects were classified using Visual Geometry Group (VGG)-16 deep learning structure.

Further a work based on convolutional neural network developed using VGG architecture [15] was found to be efficient in identifying the tyre defects. This method was able to identify the defects following three phases of processing the data. A deep learning based solution is provided in [16] to automatically detect the tyre defects using a densely connected convolutional neural network working on images from a smart phone. Further, a methodology using GoogleNet architecture is proposed in [17]. This method is found to be highly accurate in detecting the tyre defects automatically. A survey on the various methods provided comprehension on the use of various technologies and application of machine learning and deep learning methods to automatically detect/predict the tyre defects affected by several parameters.

Unlike previous existing methods, the paper proposes a pattern recognition framework utilizing the advantages of feature integration and ensemble classification methods to improve the task of defect/crack detection in tyres. As mentioned in the introduction section, the degradation in tyre is a result of various parameters acting on it and the effects can be observed as punctures, cracks, irregular wear, cuts, and bulges. The work presented here focuses on detecting the cracks on the tyres using appropriate texture descriptors and machine learning ensemble classification model. The detection can be mapped further towards taking appropriate action required.

The contributions of this paper are:

- Derive and frame robust texture descriptors to describe the detailed texture characteristics of tyre surfaces.
- Analyse the features to understand the variations in the texture on tyres.
- Effective discrimination of normal and cracked tyre surfaces using ensemble learning by combining the predictions of multiple classifier models.
- Quantitative assessment of the ensemble learning methods for their validity and reliability.

The rest of the paper is organized as following. Section 2. provides details about methodology formulation. Results and discussion are presented in Sec. 3. and finally Sec. 4. concludes the paper.

2. Methodology Formulation

Identifying the defects in tyres requires a significant analysis of the tyre surfaces for any variations/deformation occurred. Deriving texture features from the tyre surfaces and their analysis can effectually aid in identifying the deformations in the surface characteristics of tyres as they are good in capturing the variations in intensity levels/gradients of the pixels. These variations captured can be the attributes that can easily discriminate between the normal and damaged/cracked tyre surfaces. Further, deriving the features from the images that can represent the variation of the tyre surfaces at global and local level enhances the performance of the tyre defect recognition system. Thus, the proposed work on identifying the defects/damages in tyre is a pattern recognition task that derives the texture features from the tyre surface images and builds a machine learning classifier model to identify and categorize the tyre surfaces into normal or defective. The formulation of methodology for the proposed system is displayed in Fig. 1.

The details of the process are presented in the subsequent subsections.

2.1. Materials

The proposed work on Tyre Defect Detection (TDD) and classification was implemented on the tyre surface images acquired from the Kaggle dataset. The dataset has a total of 1028 images of which 537 images were captured from defective tyre surfaces with cracks and remaining 491 were the normal surface images. An observation of the images shows:

- The variations in the intensity of the cracked surfaces,
- Variations in the resolution (dimension) of the images,
- Variations in illumination when the images are captured and low contrast. So, a methodology has to be framed that works effectively subjected to the variations mentioned.

2.2. Pre-processing

As the tyre surface images are with variable resolution and low contrast, they are resized and applied to contrast enhancement techniques. With low contrast it is hard to identify the variations in image. The enhancement techniques adjust the intensity (brightness and darkness) levels to improve the quality of the images. The pixel values in a low contrast images are defined within a narrow range, so the contrast enhancement methods distributed the pixel values over a wider range. Some of the widely used enhancement techniques are [18] and [19]:

1) Gamma Transformation (GT)

The gamma transformation applied to an image $I(x,y)$ carries out exponential operation to saturate the top one percent and bottom one percent of the image pixels. The transformed image $I_p(x,y)$ is related to $I(x,y)$ by:

$$I_p(x,y) = c \cdot I(x,y)^{\gamma}, \qquad (1)$$

where c and γ (Gamma) are constants.

Depending on the value of γ, the intensity values of the image are either brightened or darkened. Whenever $\gamma < 1$, the pixels in the output image become brighter and when $\gamma < 1$, they become darker. With $\gamma < 1$, $I_p(x,y) = I(x,y)$. For better results, the γ must be appropriately chosen. For low contrast images, the brightness levels of the pixels have to be modified to have better visualization and representation. Normally c is made 1 and γ is made greater than 1 ($\gamma = 2.2$).

2) Histogram Equalization (HE)

It is one of the frequently used procedure to improve the contrast of an image $I(x,y)$ because of its efficacy. Histogram equalization depends upon the cumulative distribution function (*cdf*) and it will alter the contrast of an image by varying the distribution of the intensity

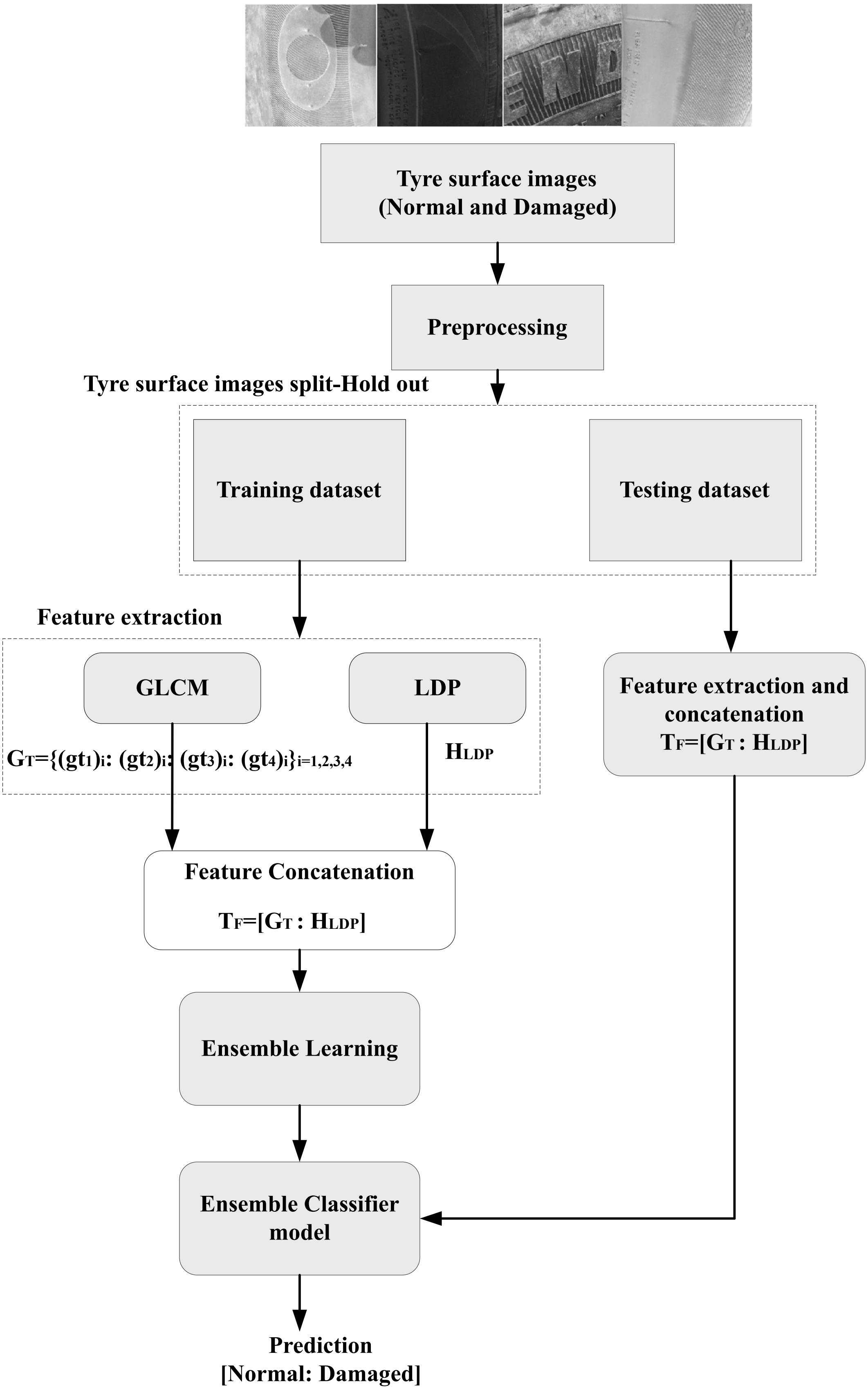
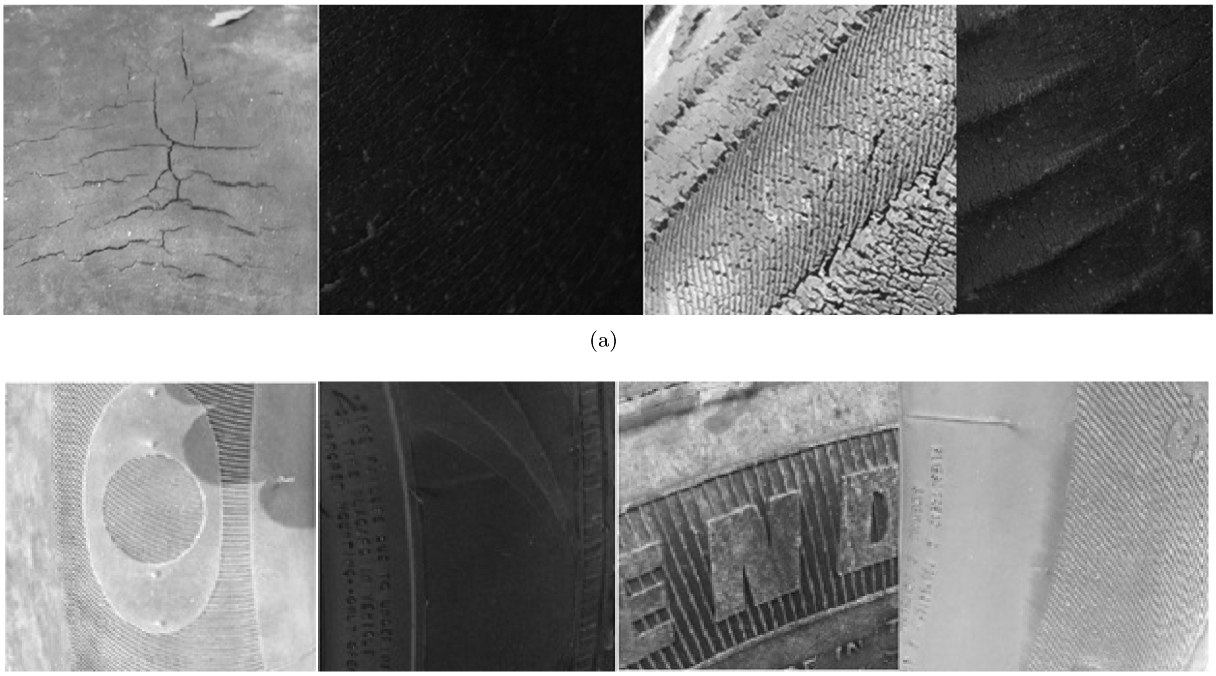


Fig. 1: The proposed framework for analysis and detection of tyre cracks.



(a)

(b)

Fig. 2: Sample images indicating the variations in resolution and illumination captured from normal tyre surfaces (a) and defective tyre surfaces (b).

levels. The resultant image after histogram equalization is:

$$I_p(x,y) = \left(\frac{cdf\,(I\,(x,y) - cdf_{min})}{N - cdf_{min}}\right) x\,(L-1)\,, \quad (2)$$

where N and L are size of the image and number of gray levels respectively

3) Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE is the adaptive histogram equalization method that enhances the contrast of the image locally without causing saturation. The method operates on smaller regions of the images i.e., the image is divided into distinct regions and contrast of region is enhanced using HE. This method solves the problem of noise amplification and preserves the edges.

The contrast enhanced image with better information is analysed to check the suitable texture features that can be derived from the images for good representation.

2.3. Texture Feature Extraction

Analysing the tyre surface images is important to identify the damages on the surfaces like cracks. This requires the images to be represented efficiently using descriptors that provide detailed information about the characteristics of the surfaces. It is found that the texture features provide a better understanding as it represents the spatial relationships between the pixels and describes the structure of the texture such as fine, coarse, smoothness, grained. The literature indicates the availability of methods that describe the texture using numerical quantities such as statistical methods and edge response based methods. These methods provide local descriptions or micro textures of the image that are very apt for the proposed method that aims in identifying the damages or cracks on tyre surfaces. The texture features are proved successful in the domains of healthcare [20] and [21], document analysis [22] and [23], content based image retrieval [24], industrial product inspection [25] and [26] etc. This paper focuses on integrating the strengths of statistical: Gray Level Co-occurrence Matrix (GLCM) and edge response based: Local Directional Pattern (LDP) texture features to provide detailed information about the characteristics of tyre surfaces for better differentiation of normal and damaged tyre surfaces.

- Gray Level Co-occurrence Matrix (GLCM)

  GLCM [27], also known as the gray level spatial dependence matrix is a statistical method of analysing the texture in images. This approach is based on the second order statistics that work on pairs of pixels with a specific spatial relationship existing between them [28] and [29]. This

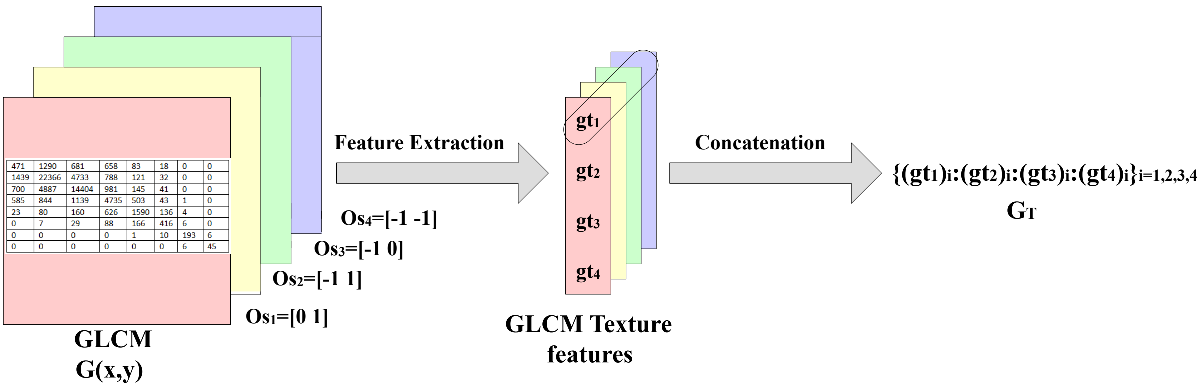


Fig. 3: Texture feature extraction from GLCM.

process involves converting an image in to an array/matrix $G(x,y)$ whose elements represent the frequency n_{xy} of a pixel having an intensity value u separated from another pixel with intensity value v at a distance D/offset in the direction θ.

$$G\left(x,y\right) = \left[n_{xy}\right]_{x,y=1}^{N}, \tag{3}$$

where $N \times N$ is the dimension of $G(x,y)$.

Here, for each contrast enhanced image four GLCM arrays $\{G(x,y)_i\}_1^4$ are framed for $\theta = [0°, 45°, 90°, 135°]$ with $D = 1$ as indicated in Tab. 1. D was chosen to be '1' as the extraction and analysis of finer texture requires a smaller value of D, larger D leads to the extraction of coarser texture. Finer texture provides more detailed information and can lead to better detection of defects on tyre surface.

Tab. 1: GLCM arrays with different offsets and directions.

GLCM	θ	D/Offset
$G(x,y)_1$	0°	[0 1]
$G(x,y)_2$	45°	[−1 1]
$G(x,y)_3$	90°	[−1 0]
$G(x,y)_4$	135°	[−1 −1]

From each $G(x,y)$ array four features: Contrast, Correlation, Energy and Homogeneity are extracted [30] using Eq. (4), Eq. (5), Eq. (6) and Eq. (7) that represent the texture of the image.

$$\text{Constant} = \sum_{x=1}^{N}\sum_{y=1}^{N} \left|x-y\right|^2 G\left(x,y\right), \tag{4}$$

$$\text{Correlation} = \sum_{x=1}^{N}\sum_{y=1}^{N} \frac{\left(x-\mu_x\right)\left(y-\mu_y\right)G\left(x,y\right)}{\sigma_x\sigma_y}, \tag{5}$$

where μ_x, μ_y, σ_x, σ_y are mean and standard deviation respectively:

$$\text{Energy} = \sum_{x=1}^{N}\sum_{y=1}^{N} \frac{G\left(x,y\right)}{1+\left[x-y\right]}, \tag{6}$$

$$\text{Homogeneity} = \sum_{x=1}^{N}\sum_{y=1}^{N} \frac{G\left(x,y\right)^{\square}}{1+\left[x-y\right]}, \tag{7}$$

Thus, for every image 16 texture features are extracted and concatenated to form a single feature vector G_T.

$G_T = (gt_1)_i : (gt_2)_i : (gt_3)_i : (gt_4)_{i_{i=1,2,3,4}}$ with $gt_1 =$ Contrast, $gt_2 =$ Correlation, $gt_3 =$ Energy and $gt_4 =$ Homogeneity. The process of texture feature extraction from GLCM is illustrated in Fig. 3.

- Local Directional Pattern (LDP)

Finding efficient features to represent the surface image of the tyre is important to identify the defect. Local features have proved to be better than global level features for image representation [31] and are also robust to work with images captured under uncontrolled environments. The proposed work uses LDP which is a local feature extraction method that considers the edge responses obtained in all directions for better stability. That is the method relies on directional information rather than intensity levels.

The process involves application of Kirsch kernels [32] of dimension 3×3 in eight different orientations [K1, K2, K3, K4, K5, K6, K7, K8] to obtain eight edge responses [ER1, ER2, ER3, ER1, ER2, ER3, ER1, ER2] specific to a respective direction.

Here each pixel of the input image is encoded using eight-bit binary code. The process is illustrated in Fig. 4. As LDP is a local feature extraction method, the Kirsch kernel is slided on the input

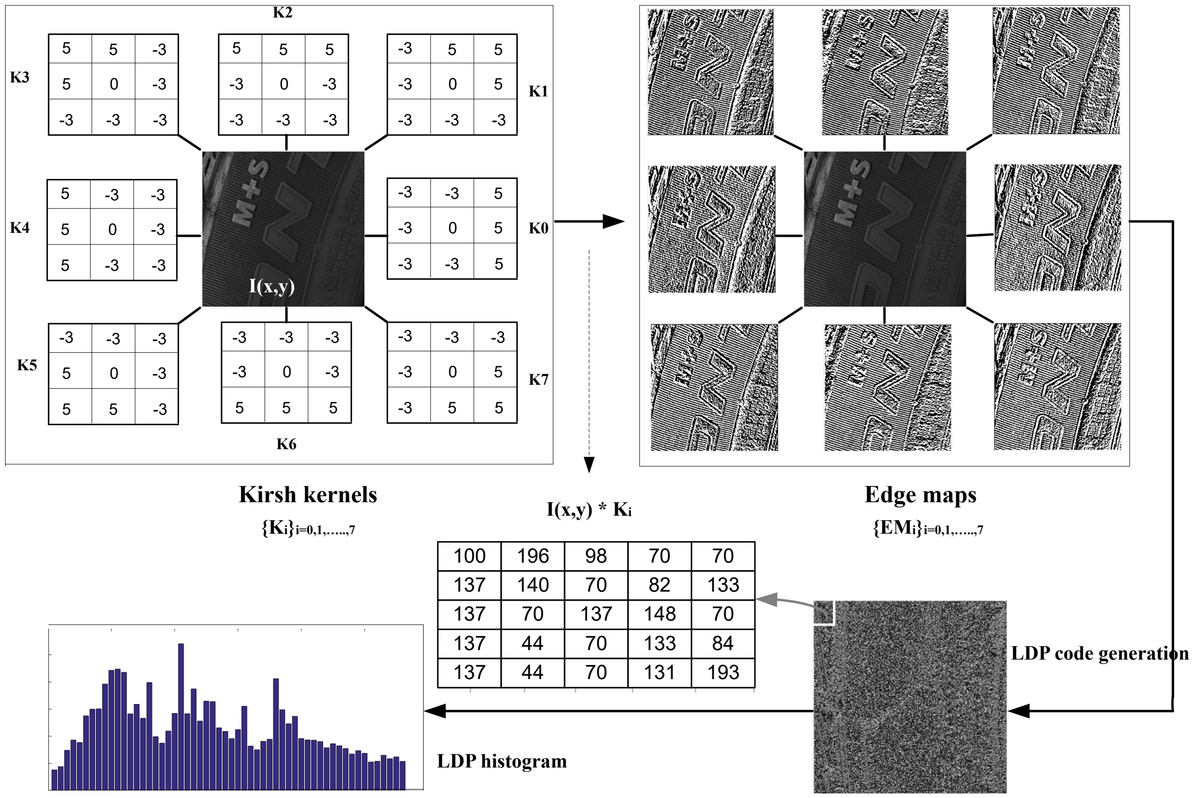


Fig. 4: Texture feature extraction from LDP.

image covering every image patch of size 3×3 with a stride of 1. The sliding is done over the complete image. With every slide, convolution of image patch and Kirsch kernel is performed to find the binary code and the centre pixel of the image patch is replaced by the binary code. Here it is important to identify the significant l directions to generate local directional pattern. So, the peak l directional bits s are set to one while the remaining $(8-l)$ bits of the LDP are made zero. The LDP code thus derived is:

$$LDP = \sum_{j=1}^{7} s_j \left(m_j - m_l \right) x \, 2^j, \tag{8}$$

where, $s_j(\alpha) = \begin{cases} 1 & \alpha \geq 0 \\ 0 & \alpha < 0 \end{cases}$, m_l is the l^{th} most important directional response.

Finally, from the encoded image a histogram of LDP H_{LDP} is found that form the feature set.

The extracted texture features G_T and H_{LDP} are concatenated to form a feature vector $T_F = [G_T : H_{LDP}]$ that assimilates the information of both the features to discriminate the images efficiently to identify the defects in tyres. The concatenated feature vector T_F is later submitted to the ensemble learning classifier algorithms for classifier model creation and testing.

2.4. Ensemble Learning (EL)

Ensemble learning [33] is a machine learning approach formulated to enhance the predictive performance of pattern recognition system by merging the predictions of multiple classifier models. EL has found to be significant in effective predictions and has proved its ability in several domains such as nondestructive testing [34], healthcare [35] and [36], detection of landslides and natural disasters [37] and [38], stock financial frauds [40], affective computing [41], anomaly detection [42] etc., Ensemble Learning is categorized into: Bagging, Stacking and Boosting methods. The bagging and boosting methods are frequently used approaches for ensemble learning. The idea behind these approaches and the details of the methods is provided in the subsequent paragraphs. market predictions [39], financial frauds [40], affective computing [41], anomaly detection [42] etc., Ensemble Learning is categorized into: Bagging, Stacking and Boosting methods. The bagging and boosting methods are frequently used approaches for ensemble learning. The idea behind these approaches and the details of the methods is provided in the subsequent paragraphs.

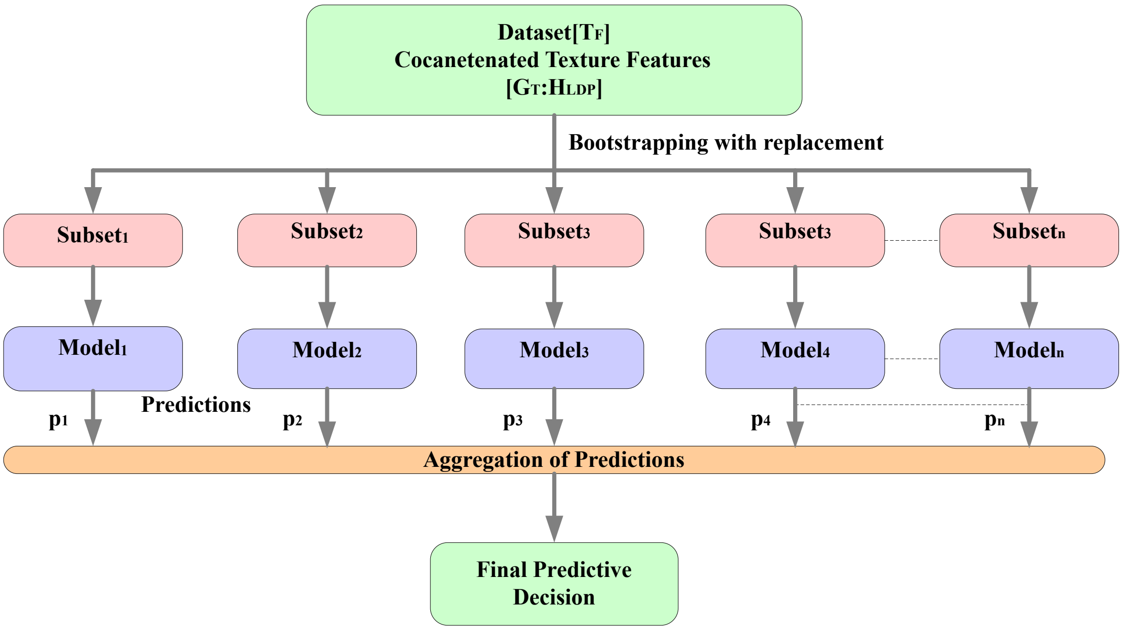


Fig. 5: Framework of Bagging ensemble method.

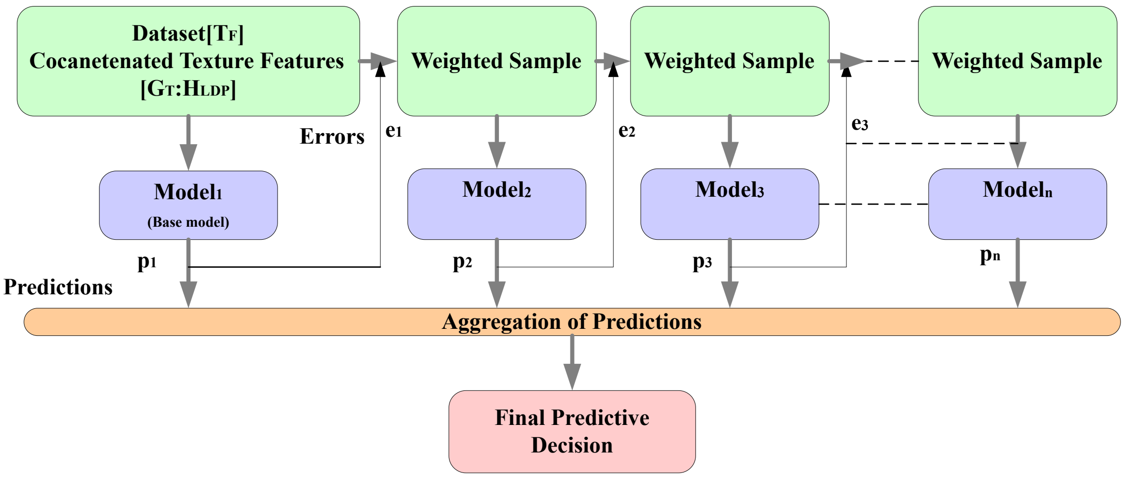


Fig. 6: Framework of Boosting ensemble method.

1) Bagging

The main elements of Bagging are Bootstrap and Aggregation. This approach considers one machine learning algorithm (relatively weak) to train with subsets of the original training dataset generated using the bootstrap sampling with replacement to create different classifier models. These classifier models are further used for testing and the final predictive decision is made based on the aggregation of the predictions of the individual models. The aggregation rule can be either voting or averaging. Some of the algorithms available to work based on this method include Decision trees, Random forest and Extra trees. The principle of Bagging is illustrated in Fig. 5.

2) Boosting

Boosting follows a sequential process where it tries to reduce the prediction errors of the classifier model. This approach tries to build a strong classifier model combining weak classifiers. To start with, the approach considers the training dataset and equal weight assignment is done on the dataset and builds a base (weak) model to give predictions. The errors obtained after the predictions are observed, the weights are modified (increased) for the data samples which are misclassified. Further a new model is created to make the predictions and it corrects the errors caused by the previous model. As a subsequent process multiple classifier models are built, each trying to correct the errors generated by the previous models. correcting the errors that were produced during the previous predictions. The final prediction is by the final model built using weighted average of all the previous models. Adaboost, Gradient Boosting (GBM), Extreme Gradient Boosting (XGBM) and Light Gradient Boosting (LGBM) are the boosting algorithms that create build a strong classifier model to improve predictive performance. The principle of Boosting is illustrated in Fig. 6.

The ensembles classifiers with boosting and bagging algorithms are trained with suitable parameters and tested for its performance. Here, the work also checks for the presence of cracks on the tyres using appropriate descriptors and machine learning classification model. The detection can be mapped further towards taking appropriate action required.

3. Results and Discussion

The proposed work focuses on identifying/predicting the cracks on the tyre surfaces formed due to various reasons. The work is implemented based on the pattern recognition model that aids in providing appropriate action required. This model makes use of appropriate texture features and ensemble classifiers.

As mentioned in the materials section, the images captured are subjected to variations in the intensity, dimension and contrast. That required the use of preprocessing techniques for effective representation. Initially all the images were converted to gray scale and resized to have uniform dimensions. Further contrast enhancement techniques such as Gamma Transformation (GT), Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) were used to improve the contrast and overcome the variations in intensity. The enhancement techniques were qualitatively and quantitatively assessed for its improvement and the method with best result was considered to continue with the further process. The role of enhancement techniques was also investigated to know their importance in differentiating the cracked tyre surfaces from the normal ones. Figure 7 displays the resultant images after enhancement process.

These images are analysed further using the measures Entropy, Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR), Absolute Mean Brightness Error(AMBE) and Gray level energy [43]. The measures are computed using the equations [9], [10], [11], [12] and [13]:

$$\text{Entropy} = -\sum_{i=0}^{G-1} p_i \ln p_i, \tag{9}$$

G is the number of gray levels, p_i is the probability of a image pixel having a gray level i.

$$\begin{aligned}&\text{MeanSquaredError} =\\ &= \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left(I_p\left(x,y\right) - I\left(x,y\right)\right)^2,\end{aligned} \tag{10}$$

$M \times N$ is the size of the image, $I(x, y)$ and $I_p(x, y)$ represents the actual and contrast enhanced images respectively

$$\begin{aligned}&\text{PeakSignaltoNoiseratio} =\\ &= 10 \log_{10} \left(\frac{(G-1)^2}{MSE} \right),\end{aligned} \tag{11}$$

$$AMBE = ||E(B) - E(A)|, \tag{12}$$

$E(B)$ and $E(A)$ are the mean gray levels of the enhanced and actual images represented as:

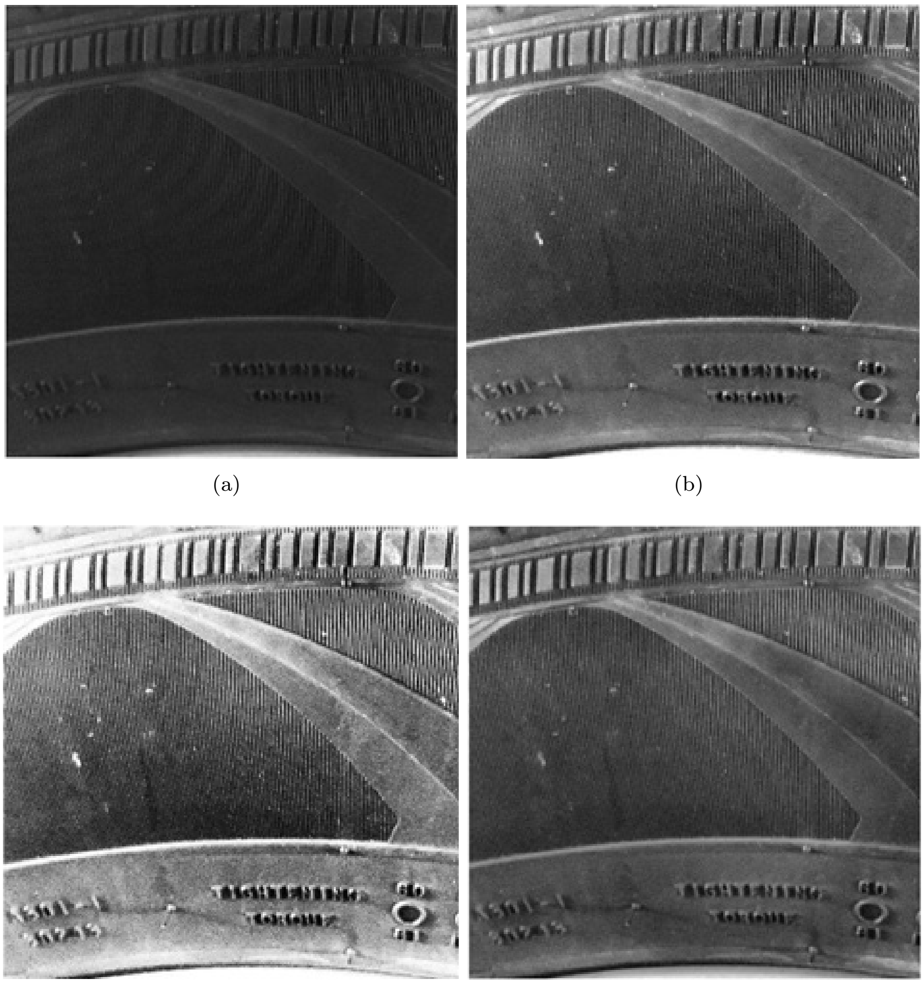
$$\begin{aligned}E\left(B\right) &= \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I_p\left(x,y\right),\\ E\left(A\right) &= \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I\left(x,y\right),\end{aligned} \tag{13}$$

$$\text{Gray Level Energy (GLE)} = \sum_{i=0}^{G-1} p_i^2. \tag{14}$$

An observation on the quantitative measures indicates the higher values in entropy and PSNR while lower values in MSE and AMBE for CLAHE . Thus the images were enhanced using CLAHE for further process of feature extraction.

From the data set holding 1028 images, all were preprocessed: $I_p(x, y)$. Later the images $\{I_p(x, y)_i\}_{i=1}^{1028}$ were divided using hold out into training set and testing set with a ratio of 70:30. Further the images of both training and testing sets were applied to feature extraction module to derive texture features based on GLCM: $G_T = \{(gt_1)_i : (gt_2)_i : (gt_3)_i : (gt_4)_i\}_{i=1,2,3,4}$ and LDP: H_{LDP}. To have a better image representation and discrimination between the normal tyre surfaces and damaged (cracked) the features were concatenated/integrated to form feature vector $T_F = [G_T : H_{LDP}]$.

Subsequent to this process, as stated above the features derived from the normal and damaged tyre surfaces were investigated with respect to image enhancement to understand their significance. It revealed that, the features extracted from the enhanced images are more significant and were able to distinguish aptly the tyres belonging to the normal or cracked categories. Figure 8 displays the feature space that exhibits the importance of image enhancement in discrimination.



(a) (b) (c) (d)

Fig. 7: Contrast enhancement results with: (a) depicting the original image while, (b) gamma transformation output, (c) histogram equalization and (d) contrast Limited Adaptive histogram equalization.

Tab. 2: Contrast enhancement performance measure.

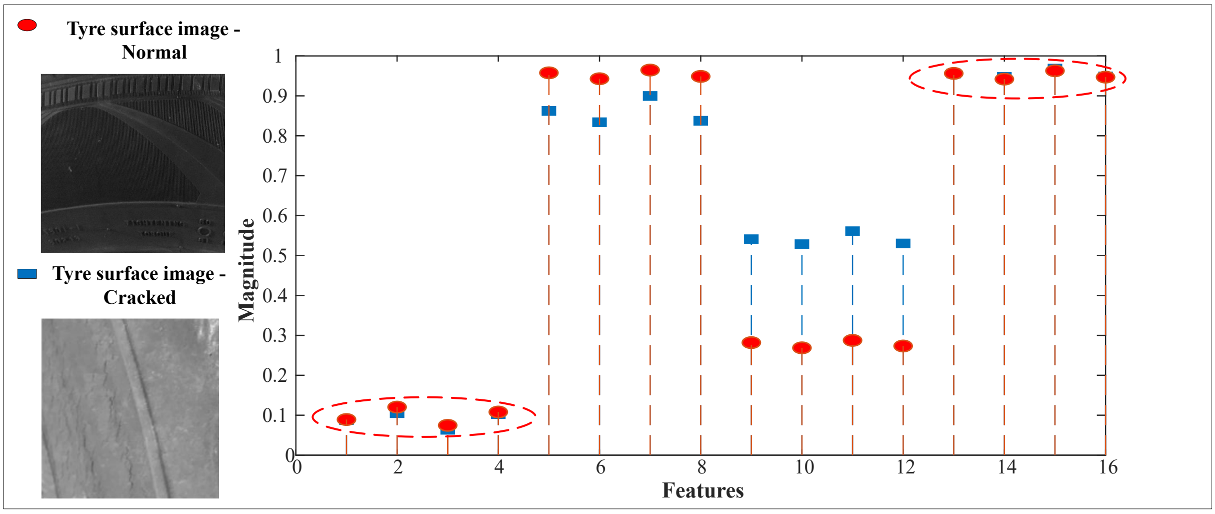
Measures	Entropy	MSE	PSNR	AMBE	Gray level energy
Gamma transformation	5.6362	2966.1	13.4089	45.2279	0.1301
Histogram equalization	5.3469	10747	7.8179	83.3038	0.052281
Contrast Limited Adaptive histogram equalization	7.2099	2089.3	14.9307	37.8891	0.13503

In feature space presented in Fig. 8(a), the blocked features in red dotted lines indicate the overlap of the features extracted from images before enhancement. This clearly specifies the presence of ambiguity in differentiating the normal and cracked tyre images, whereas the features extracted after enhancement (Fig. 8(b)) there is a clear distinction between the images. Thus, the enhancement process plays a crucial role in this proposed framework.

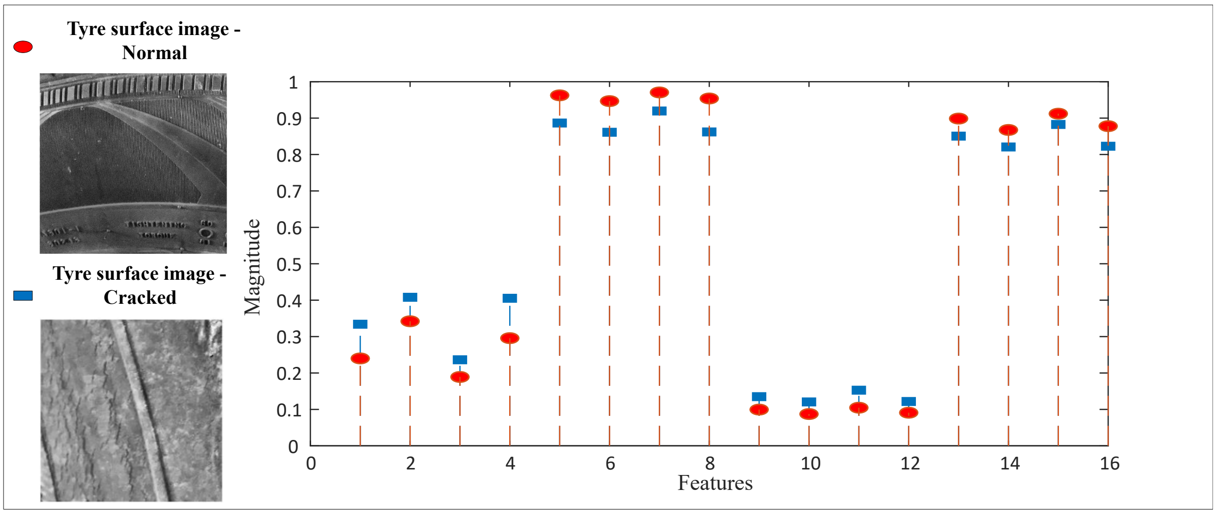
Now the feature vectors derived $T_F = [G_T : H_{LDP}]$ are provided to the ensemble learning module with boosting and bagging methods for classifier model creation and validation.

(i) For creating the ensemble classifier models, the ensemble learning methods/algorithms such as Bagging Classifier (BGC) with base estimators (a) Support Vector Machine (SVM) and (b) k Nearest Neighbour (kNN), Random Forest Classifier (RFC), Extra Trees Classifier (ETC), Extreme Gradient Boosting (XGB), Adaboost (ADA), Gradient Boosting (GBC) and Histogram Boosting (HBC) were used.

These ensemble classifier algorithms were trained with the appropriate parameters. At the start, the bagging classifier was trained with the two base estimators: SVM and kNN. During the process, the number of estimators, maximum number of features, maximum



(a)



(b)

Fig. 8: Feature space with features extracted from (a) actual images and (b) enhanced images.

number of samples, kernels of SVM and the number of neighbours in kNN were tuned and selected. The base estimator SVM with radial basis function kernel and kNN with three neighbours provided the better performance during the process. In case of Adaboost method, number of estimators, learning rate and the base estimator parameter were tuned for better performance.

Later decision tree based methods such as Random forest, Extremely random tree classifier, Gradient boosting, Extreme gradient boosting and Histogram boosting were trained. Random forest, an ensemble of decision tree classifiers is trained by adjusting the parameters that specify the number of trees, depth of a tree, number of samples for splitting an internal node and the criteria that specify the quality of the split. Here the criteria help in finding the best split so as to build a best decision tree. During training Gini index was selected as the criteria. Subsequently, an extremely random tree classifier was also trained with Gini index. Then the gradient boosting and Extreme gradient boosting methods that work by boosting the weak learners adapting gradient descent framework were trained to find the best solution. The key parameters of the Histogram gradient boosting which is devised based on the application of the binning concept on the decision tree is tuned by varying the learning rate, maximum depth and the number of iterations.

(ii) Once the ensemble classifier methods were trained or ensemble classifier models were created, the models are to be tested using the samples from the testing data set images. Henceforward, it is very important to assess or evaluate the models for validity and reliability. This step is crucial for developing an effective classifier model. Through the reliability, a level of confidence can be obtained on the models

Tab. 3: Performance metrics from ensemble classifier methods.

	Accuracy (%)	Precision (%)	Recall (%)	MCC	AUC (%)	Kappa	F1-score
BGC_SVM(rbf)	66.87	76.06	66.87	0.2722	66.12	0.2490	69.55
BGC_kNN	68.62	76.87	68.62	0.4451	72.96	0.4008	69.08
RFC	63.38	73.17	63.38	0.3602	68.32	0.3140	63.68
ETC	63.08	72.63	63.08	0.3511	67.89	0.3070	63.40
ADA	70.46	76.78	70.46	0.4570	73.80	0.4242	71.04
GBC	68.31	75.67	68.31	0.4271	72.13	0.3898	68.85
XGB	67.69	75.70	67.69	0.4232	71.85	0.3822	68.19
HGB	69.85	78.58	69.85	0.4760	74.50	0.4263	70.26

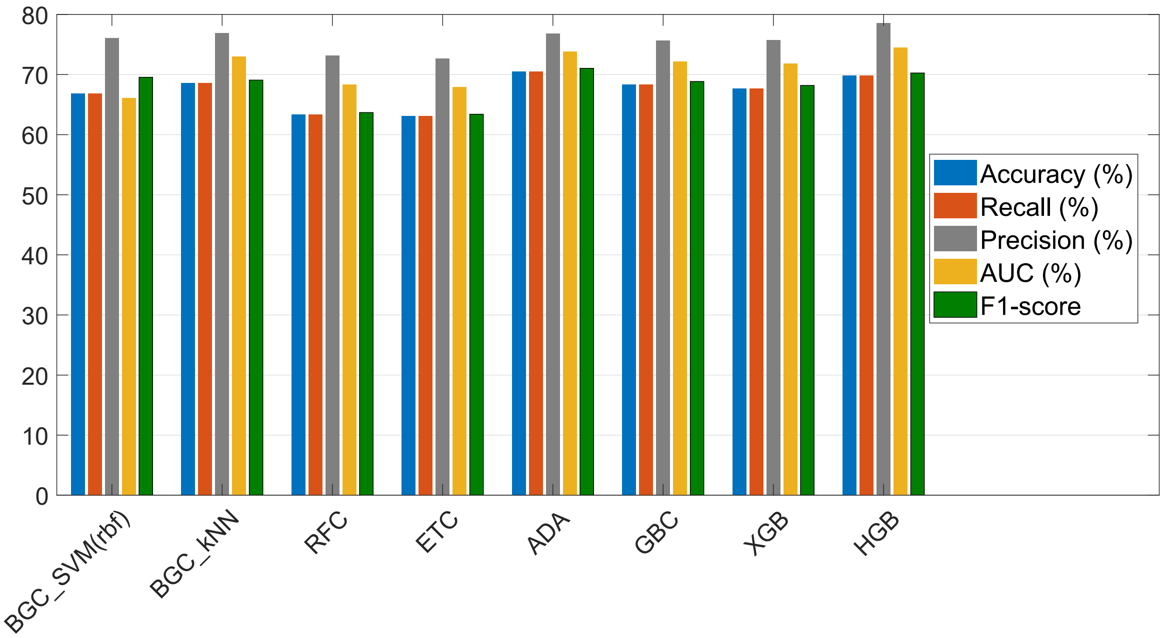


Fig. 9: Performance metrics to assess validity of the models.

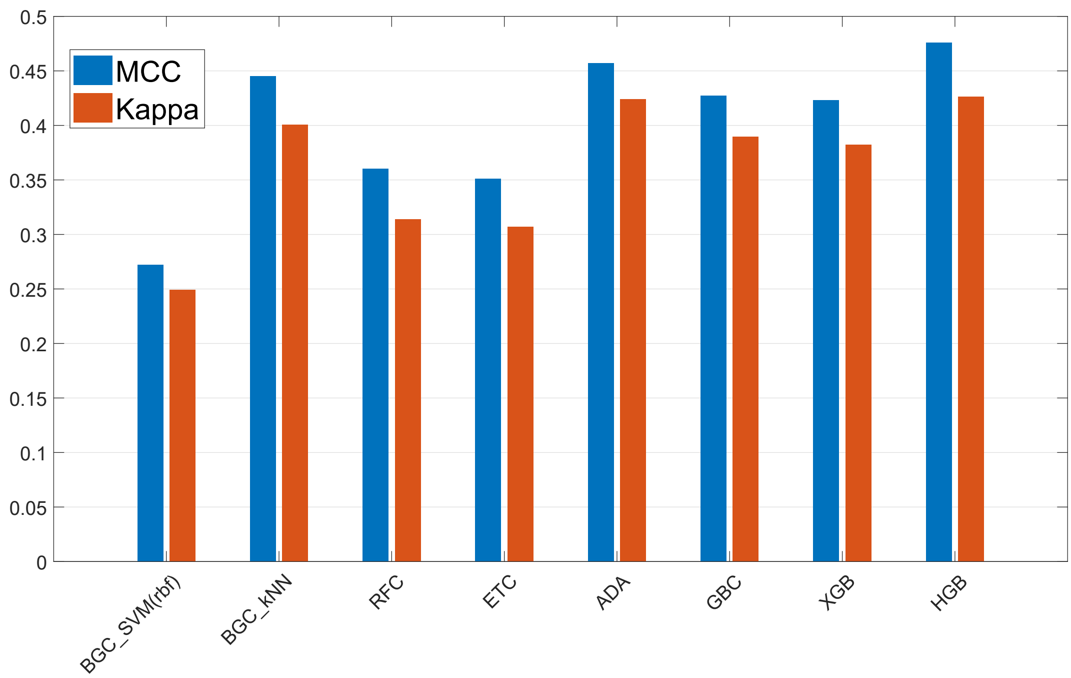


Fig. 10: Performance metrics to assess reliability of the models.

for their predictions whereas validation indicates how good are the models in providing better accuracy. The validation was carried through the process of quantifying the performance of the model based on the metrics [44]: Accuracy (Ac), Recall, Precision, Area under the Curve (AUC) and F1-score. Matthews Correlation Coefficient (MCC) and Kappa scores were selected for assessing the reliability. These metrics are computed by generating a contingency table/confusion matrix indicating the number of correct classifications and miss classifications and the elements of the confusion matrix indicate True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The computation expressions for computing the metrics are provided in the equations Eq. (11) through Eq. (17):

$$\begin{gathered}\text{Accuracy\_(Ac)} = \frac{TP+TN}{TP+TN+FP+FN}, \\ Range = \begin{bmatrix}0 & 1\end{bmatrix},\end{gathered} \tag{15}$$

$$\begin{gathered}\text{Precision} = \frac{TP}{TP+FP}, \\ \text{Range} = \begin{bmatrix}0 & 1\end{bmatrix},\end{gathered} \tag{16}$$

$$\begin{gathered}\text{Recall} = \frac{TP}{TP+FN}, \\ \text{Range} = \begin{bmatrix}0 & 1\end{bmatrix},\end{gathered} \tag{17}$$

$$\begin{gathered}MCC = \frac{TP \cdot TN - FP \cdot FN}{x}, \\ \text{where} \\ x = \\ \sqrt{((TP+FP)\cdot(TP+FN)\cdot(TN+FP)\cdot(TN+FN))}, \\ \text{Range} = \begin{bmatrix}-1 & 1\end{bmatrix},\end{gathered} \tag{18}$$

$$\begin{gathered}\text{F1} - \text{score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}, \\ \text{Range} = \begin{bmatrix}0 & 1\end{bmatrix},\end{gathered} \tag{19}$$

$$\begin{gathered}\text{Kappa} = \frac{Po - Pe}{1 - Pe}, \\ \text{with} \\ Po = Accuracy(ACC), \\ Pe = \\ \frac{(TP+FN)\cdot(TP+FP)+(FP+TN)\cdot(FN+TN)}{TP+TN+FP+FN}.\end{gathered} \tag{20}$$

Area Under the Curve (AUC) is computed using the receiver operator characteristics, which is a plot of true positive rate vs false positive rate. The results of the quantitative performance are tabulated in Tab. 3.

The results are to be analysed further to understand the performance of the classifiers in identifying the defective tyre surface. Bar charts are plotted for comparing the performance of all the classifier models with respect to all the metrics considered and the same are displayed in Fig. 9 and Fig. 10.

An observation of Accuracy indicates an average value of 67.28 % and the best Accuracy of 70.46 % is provided by ADA method. To have effective performance analysis, Precision and Recall are to be observed. The results indicate that all the models were able to provide a Precision greater than 72 % that is the fraction of positive predictions that are indeed true and Recall greater than 63 % indicating the effectiveness of the models in correctly classifying the positive samples. The best Precision and Recall were provided by HGB and ADA methods with 78.58 % and 70.46 % respectively. The highest AUC of 74.5 % is reported by HGB classifier model. An overall performance score was provided by F1 measure that combined Precision and Recall. ADA provided considerably high F1 score of 71.04 %. In case of reliability, HGB provided MCC and Kappa values of 0.4760 and 0.4263 respectively. A Kappa value of 0.4263 indicates there is a 42.63 % of agreement between the actual class labels of the tyre surfaces and predictions of the HGB model and there is a 47.60 % of correlation between the actual and predicted outputs.

An observation of the performance of individual classifier models with respect to all the metrics indicated a notable performance from the ADA and HGB models.

4. Conclusion

This paper presented a methodology based on pattern recognition to identify and differentiate the cracked tyres from the normal tyres based on the analysis of the tyre surface texture patterns. The proposed method utilized the strengths of GLCM, a statistical texture descriptor and LDP, edge response based descriptors by integrating them for efficient representation of textures. These features were trained and tested using the ensemble classifier models with bagging and boosting methods on the tyre images obtained from the Kaggle dataset. The experimental results were analysed to assess the validity and reliability of the ensemble classifier models. The results indicated the acceptable performance of Adaboost and Histogram boosting methods that provided Accuracy, Precision, Recall and F1 score greater than or equal to 75 % while MCC and Kappa values greater than 40 %. These measures signify the effectiveness of combining the local texture features for detailed representation and merging of the predictions of multiple classifier models in ensemble learning for better predictive performance.

Author Contributions

V. G. V. M. conceived the idea, developed the methodology, performed the simulations with the data, validated results and wrote the manuscript. A. N. J. R. provided critical feedback and helped shape the research, analysis and manuscript.

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Appendix A

Tab. 4: List of abbreviations.

GLCM	Gray Level Co-occurrence Matrix
LDP	Local Directional Pattern
RFID	Radio Frequency IDentification
TWD	Tyre Wear quantity and Difference
VGG	Visual Geometry Group
TDD	Tyre Defect Detection
GT	Gamma transformation
HE	Histogram Equalization
CLAHE	Contrast Limited Adaptive Histogram Equalization
GT	GLCM based texture features
OS	Offset
ER	Edge response
K	Kirsch kernel
HLDP	Histogram of LDP
TF	Concatenated texture feature vector
EL	Ensemble learning
GBM	Gradient Boosting
XGBM	Extreme Gradient Boosting
LGBM	Light Gradient Boosting
MSE	Mean Squared Error
PSNR	Peak Signal to Noise ratio
AMBE	Absolute Mean Brightness Error
GLE	Gray level energy
BGC	Bagging classifier
SVM	Support Vector Machine
kNN	k nearest neighbor
RFC	Random Forest Classifier
ETC	Extra Trees Classifier
ADA	Adaboost
HBC	Histogram Boosting Classifier
MCC	Matthews Correlation Co Efficient
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
AUC	Area under the Curve