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Separation of gangue from limestone using GLCM, LBP, LTP and Tamura

Ore sorting is a useful tool to remove gangue material from the ore, and it increases the quality of the ore. The vast developments in the area of artificial intelligence allow fast processing of full-colour digital images for the preferred investigations. Three different colour spaces were used for analyzing of colour-texture features of limestone and associated gangue. The texture features were extracted using GLCM, LBP, LTP and Tamura. These features were computed from the co-occurrence matrices, which were derived using correlation method for RGB colour. For HSV and YCbCr colour spaces, the texture features were extracted from the luminance information and the colour features from chrominance information of the colour band. The performance of SVM with cubic polynomial kernel was better with 96.8% accuracy as compared to the traditional pattern classifiers (Linear and Quadratic Discriminant analysis) and modern classifiers KNN and weighted KNN.

Keywords: Co-occurrence matrices, colour-texture features, limestone, gangue, GLCM, LBP, LTP, Tamura, SVM and KNN

1.0 Introduction

A mining deposit is mostly composed of the minerals and the associated gangues. The identification of minerals and gangue is an essential operation for maintaining the ore quality of a mine [10]. Ore sorting has been used in mineral processing since the ancient age, with hand sorting being one of the earliest methods of minerals processing. Automatic sensor-based ore sorting [9, 29] was a major breakthrough in minerals technology and upfront beneficiation, resulting in substantial reduction in downstream costs, improvement of ore quality and exploitation of low-grade ore reserves. Several sensor-based technologies are found to be potentially useful for sorting applications that include optical sensors, electromagnetic, infrared, X-ray and laser-based sensors [28].

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Digital image processing techniques in recent times have been applied in the mineral industry in different mining operations such as online ore monitoring, particle size estimation, ore sorting and classification [39]. Image processing is a potential approach for developing an online system, which stimulates human eyes to detect gangue mineral particles in the ore based on the visual and textural properties of ores [32].

In this paper, the colour and texture features were extracted from RGB, HSV, and YCbCr colour spaces. The texture features include the features extracted using GLCM, LBP, LTP and Tamura methods. The texture features were computed both within and between colour channels. The performance ore-gangue classification was compared to linear, quadratic, SVMs and KNN classifiers.

2.0 Literature review

In recent times, research and development efforts for tracking ore properties was mainly focused on monitoring ore quality, size distributions, and ore separation on conveyor belts using various imaging techniques. Singh and Rao (2005) proposed a neural network-based approach for sorting and classification of three types namely: grey, brown and white of enriched ore encountered in the steel industry. Four textural features energy, entropy, contrast, homogeneity were extracted using grey level co-occurrence matrices (GLCM). These features were used as inputs to a radial basis neural network for classifying ore, and the overall accuracy was 88.71%[32].

Tessier et al. (2007) proposed a machine vision approach for on-line estimation of mixed rock composition. Colour features were extracted using principal components analysis (PCA) whereas texture features were quantified using both wavelet texture analysis (WTA) and grey level co-occurrence matrices (GLCM). The proposed system was classified using 3-SVM model. The first SVM model was more accurate in classifying the soft rocks, and the second SVM model classified hard and soft rock sub-images with 50% and nearly 40% accuracy. The third SVM model was used to classify soft, medium, and hard rock sub-images and resulted in 64%, 58% and 25% accuracy [36]. Song and Wang (2007) suggested a coal-gangue on-line automatic separation system based on the improved BP (back propagation) algorithm and

ARM (advanced RISC machines) by extracting mean and variance values from the ore particles. The overall error rate of the mean and variance parameter was observed as ±8% [33].

Ma (2007) suggested a revised algorithm based on wavelet transform to suppress the speckles in the gangue images, to enhance edges because the coal gangue images were always contaminated with speckles of coal dust[22]. Ma and Zang (2008) suggested a novel image processing method for separating gangues from coal with wavelet analysis. The Haar wavelet was used to reduce high frequent noises of gangue images. Gangue image edges were detected with multi-resolution edge detection. The image segmentation algorithm of self-adaptive threshold was studied by a coarse-to-fine multi-resolution wavelet transform. Embedded microprocessor ARM was adopted in the system for gangue separation and observed an overall error rate of ±8% [20].

Al-Batah et al. (2009) suggested a novel method for automatic classification of aggregate shape using moment invariants and artificial neural network. Hu, Zernike, and Affine moments were used to extract features from binary boundary and area of images. Discriminant analysis was used to select optimum features for the aggregate shape classification. A cascaded multi-layered perceptron (c-MLP) network was proposed to categorize the aggregate into six shapes.The overall accuracy of the system was calculated by taking the average of classification accuracy of all the six groups and resulted in 82.36%[1]. Ma and Liang (2009) suggested a novel application of rough set theory in image process strategy to detect the coal gangues. The image processing operations such as the denoising, enhancement, sharpening and edge detection were performed by using the rough set theory[21].

Chatterjee et al. (2010a) applied vision based techniques for predicting ore grades in a limestone mine by using principal component analysis (PCA) on 189 extracted features to reduce the dimensionality for quality parameter modeling. The mean squared error and R2 values for the grade attributes CaO, Al_2O_3, Fe_2O_3, and SiO_2 are 22.20, 3. 17, 1.02 and 48.60, and 0.89, 0.78, 0.85 and 0.87 respectively[6]. Chatterjee et al. (2010b) proposed an image analysis-based method that determines efficiently and cost-effectively, the quality parameters of material by reducing image features by applying the genetic algorithm. The mean absolute error of the best network, GA ensemble, average ensemble, and weighted ensemble were 3.347, 3.38, 3.346, and 3.346 respectively[5].

Liang et al. (2010) suggested gangue separation based on the difference of the grey scale and texture in the images of coal and gangue. Five characteristic parameters (mean, variance, skewness, kurtosis, and energy) were considered as the classification features and extracted from the grey-scale histogram. Identification of coal and gangue was performed by using the self-organizing competitive neural network algorithm and support vector machine (SVM) algorithm. The identification rate of the self-organizing competitive and the SVM neural network was 85% and 95% respectively [19]. Li et al. (2010) suggested a computer vision-based automatic separation system framework for coal and gangue. Greyscale histogram, fractal dimension, and multi-level Daubechies-4 lifting wavelet transform energy values were extracted as ore features. A 4-layer Levenberg Marquart BP Neural Network was designed to implement multi-feature fusion with an overall accuracy of 97.5% [17].

Singh et al. (2010) proposed a new approach to identifying the texture by extracting 27 numerical parameters using RGB or grey colour space of thin sections of different basalt rock samples as an input. A multilayer perceptron neural network takes those parameters as input and provides, the output, the estimated class of texture of the rock. The proposed method resulted in 92.22% accuracy in automatically identify the textures of basaltic rock using the digitized image of thin sections of 140 rock samples [31]. Khorram et al. (2011) proposed the chemical grade determination of limestone using a different combination of image features. A total of 76 features were extracted from the identified rock samples. A neural network was used as an intelligent tool for ore grade estimation. For the four grade attributes of limestone ($CaCO_3$, Al_2O_3, Fe_2O_3 and $MgCO_3$) the root of mean squared error between the observed values and the model estimated values were 0.38, 0.84, 0.15 and 0.03 and the R^2 values were 0.78, 0.76, 0.76 and 0.81 respectively [15].

Perez et al. (2011) proposed a new method to improve rock classification using digital image analysis. 14 features were selected from 36 features that were extracted using mutual information. The original image was divided into sub-images that were assigned to one class based on the selected colour and texture features using a set of classifiers in cascade. A voting process for the sub-images within the same blob was performed using rock boundary information comparison. The results were compared to previously published work on the same rock image database, and the comparison revealed that the RMSE on rock composition classification rate was decreased by 8.8% and 29.5% with previously published results [26]. Wang and Liang (2011) suggested a system to investigate the fundamental characteristics of coal and gangue based on digital image processing technology by extracting mean and variance of the greyscale histogram. A high-performance micro-controller DSP (digital signal processing) was used to improve the operational speed of the system [37].

Zhang and Zhang (2012) suggested a method of separating gangue from coal based on density by calculating volume and weight of the ores. The experiment showed that this method was suitable for recognition of coal and gangue with the size larger than $10cm^3$, with the separation accuracy up to 60% [38]. Chatterjee (2013) proposed a vision-based rock-type classification system for limestone. A total of 189 colour, morphology and textural features from the seven core components (r, g, b, H, S, I and grey) were extracted. A genetic algorithm was used for reducing 189 image features to 40 features. SVM was used for rock classification and the overall accuracy for the rock classification was 96.2 % [4].

Mu and Dong (2013) suggested a high-speed image processing of embedded system based on FPGA (field-programmable gate array) and DSP (digital signal processing) collaboration used in coal detection technology. The system extracted the image features of coal and gangue, particularly their grey scale values and the center of gravity. By analysis of the characteristics of the image, the system identified the gangue [23]. Gao et al. (2013) suggested recognizable decision algorithm based on Bayesian decision theory to calculate the threshold of the grey scale distribution histogram. RNRA (related neighbourhood pixels recognition algorithm) was proposed to recognize the gangue while they were moving on a belt conveyor. An accuracy of 96.8% was obtained by testing the recognition system on-line with a large number of randomly selected materials for many times[12]. Reddy and Tripathy (2013) proposed a model based on histogram thresholding for separation of gangue from coal. The grey scale characteristics of coal and gangue images using traditional threshold segmentation were investigated [27].

Das and Choudhury (2014) proposed a new method extending a general remote sensing approach for estimation of rock type estimation. Each image was divided into sub-images using the BQMP (binary quaternion-moment-preserving) to extract colour feature and SVM (support vector machines) for classification. The proposed method was compared to texture and colour features extracted from wavelet texture analysis (WTA) and principal components analysis (PCA) respectively. The results indicate 78.8% and 69.3% accuracy with WTA-PCA and 93.05% & 91.8% of classification accuracy for BQMP method respectively [8]. Li et al. (2015) proposed coal and gangue separation by extracting the mean value of gray histogram and the textural feature based on an adaptive window of texture analysis. These texture feature based on the best window size were extracted to recognize coal and gangue [16]. Li (2015) proposed automatic coal and gangue identification by analyzing the difference and distribution regularity of the grayscale. The training set was split into a small sample set by using improved multiple kernel fisher discriminant analysis method, which in turn calculated projection mapping by using voting strategy discrimination for the samples [18].

3.0 Methodology

The main steps involved in the proposed method are image collection, image pre-processing, image segmentation, feature selection and image recognition as shown in Fig.1. These steps are described in the following sub-sections [37].

Fig.1: Image processing based ore classification method

Image collection

Different types of samples were collected from the mine. The images of the collected samples were captured in the laboratory set up with using a digital camera under illumination system. Image captured should be of good quality to extract the feature.

Image pre-processing

The main purpose of pre-processing was to extract ROI (region of interest) image for further recognition. First, video image frames were converted into grayscale images and noise in the images were removed by median filters. The median filter considers each pixel in the image and in turn looks at its nearby neighbours to decide whether, it was representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighbouring pixel values, it replaces it with the median of those values. The median was calculated by first sorting all the pixel values from the surrounding neighbourhood into numerical order and then replacing the pixel being considered with the middle pixel value [13].

Image segmentation

After image pre-processing, image segmentation was performed to generate a binary image in which each discrete region represents an individual rock sample. The image features were extracted from individual segmented rocks. Image segmentation was performed using a global threshold value, which converts the gray image into a binary image by separating the foreground and background. The image pixels above the threshold were considered as foreground and the remaining pixels as background. The objects in the segmented image were identified using a region labelling algorithm. The features were extracted from each identified rock in an image [13].

$$BW = \begin{cases} 1, if I(i,j) < T \\ 0, otherwise \end{cases} \quad \text{... (1)}$$

Where T is the global threshold, and $I(i,j)$ is the pixel value at the i^{th} row and j^{th} column of the image I.

Feature extraction

The feature extraction process extracts, colour and texture features from individual rock samples. The colour is an important visual attribute for both human perception and computer vision and one of the most widely used visual features in the image. Mostly RGB, HSV and YCrCb colour spaces are used for describing the colour information of the image. Each colour space consists of three-dimensional spaces and colour is used as a vector in it. The various colour features such as mean, variance, standard deviation, skewness, and kurtosis were computed from the histogram of each colour band.

Texture refers to the visual patterns that have properties of homogeneity that do not result from the presence of only a single colour or intensity. It contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment. Texture features were extracted using gray level co-occurrence matrix (GLCM), local binary pattern (LBP), local ternary pattern (LTP) and Tamura features.

Gray level co-occurrence matrix (GLCM)

This approach explored the gray-level spatial dependence of texture. It first, a co-occurrence matrix was constructed based on the orientation and distance between image pixels. It was used to calculate how often pixels with gray level value i occurs horizontally adjacent to a pixel with a value j and then extracted meaningful statistics from the matrix as the texture features as shown in Fig.2. The texture features were extracted from the texture information contained in the co-occurrence matrix. Haralick had extracted 14 texture features from GLCM matrix, but homogeneity, contrast, correlation, entropy and energy features were commonly used because it was shown that the 14 features extracted were much correlated with each other [7, 14]. Homogeneity (H), Contrast (C), Correlation (Cor), Energy (E) and Entropy (N).

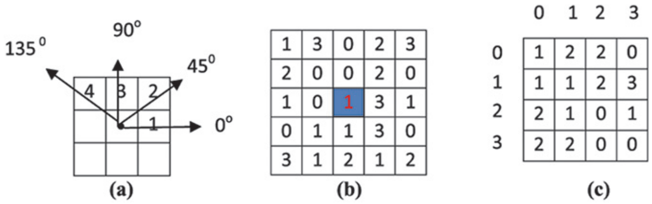

Fig.2: Gray level co-occurrence matrix computation

$$H = \sum\sum(M_t(i,j))^2 \qquad \text{... (2)}$$

$$C = \sum_{k=0}^{m-1} K^2 \sum_{|i-j|=k} M_t(i,j) \qquad \text{... (3)}$$

$$Cor = \frac{1}{\sigma_i\sigma_j}\sum_i\sum_j(i-\mu_i)(j-\mu_j)M_t(i,j) \qquad \text{... (4)}$$

Where μ_i and σ_i are the horizontal mean and variance and μ_j and σ_j are the vertical statisticsof the co-occurrence matrix M_t and $M_t(i,j)$ is the pixel at i^{th} row and j^{th} column of the matrix.

$$E = \sum_i\sum_j M_t(i,j)^2 \qquad \text{... (5)}$$

$$N = \sum_i\sum_j M_t(i,j)\log M_t(i,j) \qquad \text{... (6)}$$

These five features were normalized by the number of bins in the co-occurrence matrix M in order to fit between 0 and 1. These five features were calculated in all directions (0°, 45°, 90° and 135°). These rotation dependent features were converted into rotation independent by calculating the average in all directions.

$$\text{Average} = \frac{1}{N}\sum_{i=1}^{N} X_j \qquad \text{... (7)}$$

Where X_j was the feature in a direction and N indicates four directions.

Local binary pattern (LBP)

LBP texture analysis operator was defined, as a gray-scale invariant texture measure, derived from a common definition of texture in a local region, which labels the pixels of an image by the process of thresholding the neighbourhood of each pixel and results in a binary number [24]. In a 3×3 sub-matrix, the central pixel value was subtracted with its eight neighbour pixels value. If the resultant value was a negative value, it is encoded as 0 and the others with 1; A binary number was obtained by concatenating all these binary codes in a clockwise direction starting from the top-left one and its corresponding decimal value was used for labeling. The obtained value was then multiplied by weights given to the corresponding pixels as shown in Fig.3. Summing the obtained values gives the measure of the LBP [25]. The LBP histogram was considered as a feature descriptor of the texture and mean, variance, standard deviation, skewness, and kurtosis were computed.

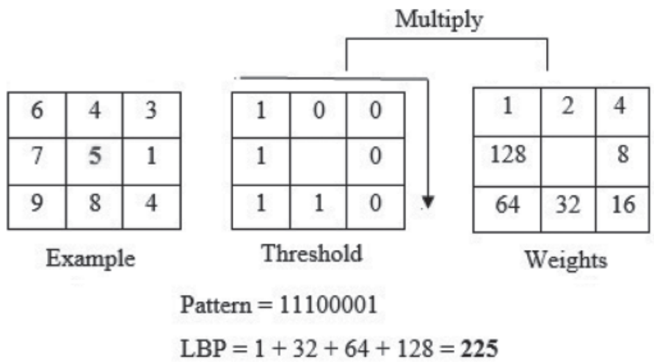

Fig.3: Calculation of LBP

Local ternary pattern (LTP)

The LBP is sensitive to noise because a small gray change of the central pixel may cause different codes for a neighbourhood in an image, especially for the smooth regions. LTP is an extension of LBP, and the neighbourhood pixel values were compared with central pixel using a threshold value, and the neighbourhood values will be assigned –1 or 0 or +1. The calculation of the positive part and the negative part was shown in Fig.4 [35].

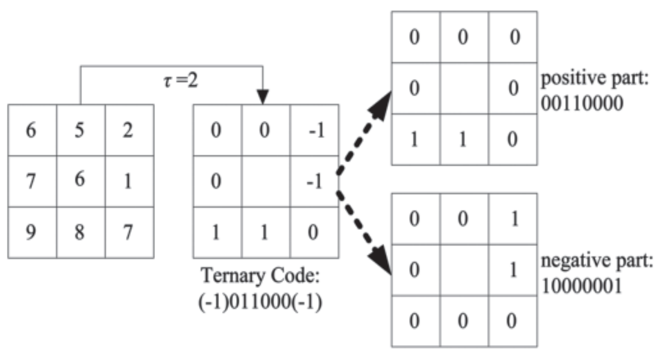

Fig.4: Calculation of the LTP

Tamura features

Tamura et al. proposed six essential texture features by taking human visual perception into consideration. The six features were defined as coarseness, contrast, directionality, linearity, regularity, and roughness. The most important features of these were mainly the coarseness, contrast, and directionality of the texture. Coarseness was designed to measure differences between coarse and fine textures. The dynamic range of gray-levels influences the contrast value of the image. Directionality is a global property over a region. It does not aim to differentiate between different orientations or patterns but measures the total degree of directionality [34].

Correlation between RGB channels

The RGB colour images were coded on three channels R, G and B. In this method; the texture features were extracted from the co-occurrence matrix derived from the same colour channel (R, R), (G, G), (B, B) and correlation between the channels (R, G), (R, B), (G, B) as shown in Fig.5 [3].

Fusion of colour and texture features

This method (Fig.6), the colour spaces HSV and YCbCr were used, where the luminance and chrominance information was stored in individual channels. Texture features were then computed from the luminance channel and other features named colour features were computed from the chrominance channel [11]. In HSV (hue, saturation, value) colour space, the chromatic information is stored in H (Hue) and S (saturation), the luminance information is stored in V (value) channel. In

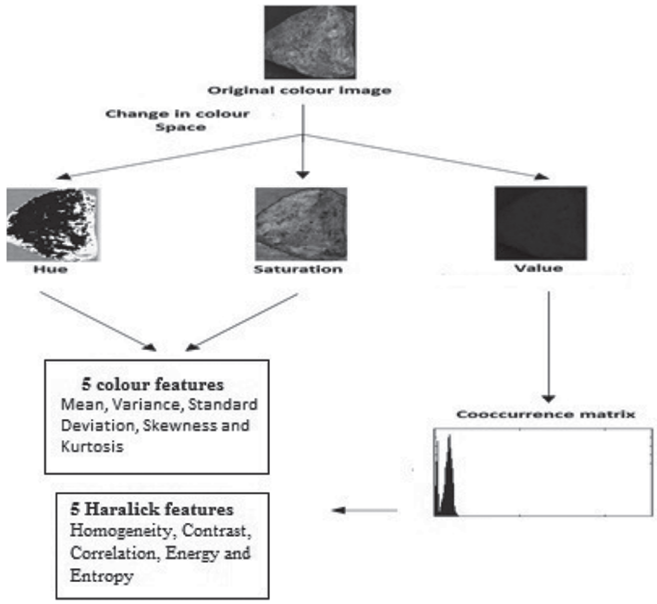

Fig.6. Illustration of the fusion of colour and texture features applied on an image

YCbCr colour space, luminance information was stored as a single component (Y), and chrominance information was stored as two colour-difference components (Cb and Cr)[3].

Image recognition

All the binary classifiers were grouped as density based and kernel-based classifiers. For density based classifiers (Linear and quadratic discriminant analysis) the output function $f(x)$ was a log likelihood ratio and for kernel-based classifiers (Nearest-Neighbour and SVMs) the output was a potential field that was related to the distance from the separating boundary.

Discriminant analysis

These classifiers work under the assumption that different classes generate data based on different Gaussian distributions. In the training phase, the Gaussian distribution parameters for each class were estimated by the fitting function and to predict the classes of new data, and the trained classifier finds the class with the smallest mis-classification cost. There are mainly two types of discriminant analysis classifiers namely – linear discriminant analysis classifier (LDA) and quadratic discriminant analysis (QDA) classifier. The QDA classifier can be considered as the generalization of LDA. Among many possible techniques for data classification, LDA is a commonly

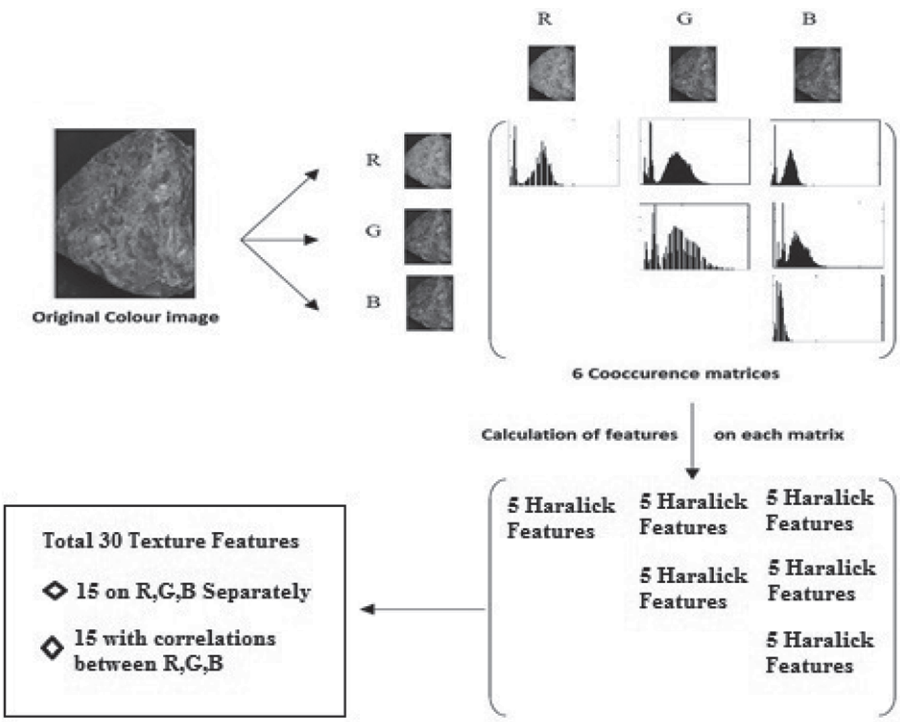

Fig.5. Illustration of the multispectral method applied to an image

Fig.7. Limestone, dolomite limestone, dolomite, quartz, hematite and limonite samples

used one. LDA was used to find the linear combination of features which best separate two or more classes of object or event. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability. Unlike LDA however, in QDA there was no assumption that the covariance of each of the classes was identical. When the assumption was true, the best possible test for the hypothesis that a given measurement was from a given class is the likelihood ratio test. Using QDA each of the covariance matrices was estimated separately, which requires a larger sample than that used in LDA to reach the same level of reliability in the estimations and hence in the predictions [30].

K-Nearest Neighbour (KNN)

In K-nearest neighbour (KNN) method, distance was assigned between all points in a data set. The data points, K-closest neighbours (K being the number of neighbours), are then found by analyzing the distance matrix. The K-closest data points were then analyzed to determine which class label was the most common among the set. The most common class label was then assigned to the data point being analyzed. In this work, three different distance measures viz., Euclidean, City block, and Cosine distance were used to study the effect of distance measurement on classification accuracy. The other variant of KNN used is weighted KNN. The weighted K-nearest-neighbour is a classification technique based on the majority voting of the neighbours. The neighbours are training points previously loaded into the cognitive classifier. The set of the K-nearest training points must first be determined by calculating the weighted distances between the test point and each training point. The weight of each feature or sensing result was determined by calculating the area under the receiver operating characteristic curve of the corresponding feature. Hence, the distance of each feature between training and test point was multiplied by the corresponding weight to obtain the relative distance between the training and test points [2].

Support vector machines (SVM)

These classifiers were based on structural risk minimization principle and statistical learning theory with an aim of determining the hyperplanes (decision boundaries) that produce the efficient separation of classes. The underlying algorithm is support vector classification (SVC), and it revolves around the perception of a "margin"- on either side of a hyperplane that divides two data classes. Maximizing the margin creates the largest possible distance among the hyperplane and the instances on either side of the hyperplane reduce an upper bound on the anticipated generalization error. It works on two types of data i.e. linearly separable data and linearly non-separable data. In the case of linearly separable data, only one hyperplane is needed for separating the data but in the case of latter, more than one hyperplanes are needed[2].

4.0 Results and discussions

Samples were collected from Lanjiberna limestone and dolomite mines, Odisha in India. For this study, a digital camera (Canon EOS 60D) was used. The images of the samples collected were taken in the laboratory set up with illumination system on a conveyor belt system. The video captured was 1088 x 1920 pixels. For the analysis, 943 images were captured from Lanjiberna limestone and dolomite mines, where limestone was intimately associated with dolomite limestone, dolomite, and quartz. A few traces of hematite and limonite were also found in the mines as shown in Fig.6.

The frames of the video were converted into a gray image, and an adaptive threshold was used to segment the foreground from background. The segmented images were then processed for identifying and labelling the individual rock present in the segmented parts using regional labelling algorithm and mapped with the colour image as shown in Fig.7. Initially, colour features were extracted from R, G, B, H, S, Cr and Cb colour bands. Texture feature were extracted from (R, R), (G, R), (G, G), (B, R), (B, G), (B, B), value (HSV colour space), Y (YCbCr colour space) and Grey using GLCM, LBP, LTP and Tamura methods.

Density based classifiers - linear, quadratic discriminant analysis and Kernel based classifiers - nearest-neighbour and SVMs were used for identification of quartzite from image-extracted features. The features extracted were used as the input parameters and the identification of mineral and associated gangue minerals were used as the output parameters of the binary classifiers. Cross-validation is a model evaluation method that is better than residuals. For the analysis 10-fold cross-validation was used, where the data set was divided into 10 subsets, and the holdout method was repeated 10 times. Each time, one of the 10 subsets was used as the test set, and the other 9 subsets were put together to form a training set. Then the average error across all 10 trials was computed. The SVM classifier was tested with various kernels (linear, quadratic and cubic polynomial kernel) to

Table 1: Classification rate using GLCM, LBP, LTP and Tamura

Texture	LDA	QDA	L-SVM	Q-SVM	C-SVM	KNN-E	KNN-C	KNN-CB	Weighted KNN
Grey (R,G,B colour and Grey texture)									
GLCM (D=1)	76.9	76.6	90.8	93.4	93.8	89.5	90.8	90.7	90.1
GLCM (D=2)	70.6	76.6	90.4	93.8	93.5	90.2	91.3	91.1	90.6
LBP	77.6	78.2	87.6	92.6	93.5	89.7	89.1	90.4	89.2
LTP	80.7	80.9	91.4	94.6	94.9	92.1	91.6	91.5	91.8
Tamura	75.5	73.1	90.8	92.8	92.5	90.6	90	90.7	90.7
HSV (H&S colour and V texture)									
GLCM (D=1)	83.4	82.4	88.6	93.0	92.5	88.4	87.4	89.2	89.4
GLCM (D=2)	82.4	81.5	89.3	92.6	93.1	87.8	86.5	89.5	89.7
LBP	66.9	69.2	78.3	85.1	86.6	82.4	81.5	84.5	84.1
LTP	69.9	68.0	79.8	88.6	89.5	84.1	85.5	85.7	87.3
Tamura	84.8	83.5	89.4	91.6	91.3	89.0	89.3	90.6	91.5
YCbCr (Cb and Cr colour and Y texture)									
GLCM(D=1)	87.6	87.5	91.8	93.8	94.2	92.1	92.8	93.0	93.3
GLCM(D=2)	86.4	87.2	92.4	94.3	94.7	91.6	91.7	92.7	92.6
LBP	84.6	85.5	91.3	94.7	94.2	92.6	91.3	93.1	92.4
LTP	85.1	82.4	91.9	95.1	95.8	93.8	93.9	93.1	92.9
Tamura	86.4	85.9	93.1	94.5	93.1	91.2	91.8	92.7	92.9
RGB (R, G and B colour and RG, RB and GB texture)									
GLCM(D=1)	75.4	75.3	90.8	94.9	94.5	90.7	90.8	90.4	91.4
GLCM(D=2)	74.1	74.4	91.7	93.7	94.2	91.7	91.2	91.4	91.3
LBP	70.0	71.0	88.9	93.4	94.2	90.6	90.1	91.2	89.6
LTP	66.0	66.6	88.6	93.2	94.9	89.6	88.7	87.5	90
Tamura	73.9	74.6	90.9	93.1	92.9	91.7	91.1	92.3	89.6
RGB (R, G and B colour and RR, GG and BB texture)									
GLCM(D=1)	74.1	77.5	93.6	94.8	94.7	92.0	91.9	93.0	91.6
GLCM(D=2)	73.8	77.0	92.9	94.9	95.0	92.7	93.1	93.1	91.4
LBP	73.0	74.9	89.7	94.9	95.0	91.5	91.3	91.8	91.6
LTP	69.2	70.5	90.3	94.6	95.3	91.1	90.4	88.7	90.6
Tamura	76.8	77.2	91.0	93.9	93.5	91.7	91.5	92.7	91.3
RGB (R, G and B colour and RR, GG, BB, RG, RB and GB texture)									
GLCM(D=1)	71.7	77.8	92.9	93.9	95.0	91.4	91.3	91.0	91.6
GLCM(D=2)	71.1	77.5	92.6	94.4	94.9	92	92.4	91.5	92.0
LBP	66.8	68.3	89.7	94.6	95.0	91.8	91.4	90.6	90.7
LTP	60.0	63.8	89.9	93.9	94.5	89.2	89.4	83.5	89.5
Tamura	74.8	75.6	91.3	93.9	93.3	91.9	91.5	92.4	90.4
HSV + YCbCr (H,S, Cb and Cr colour and V and Y texture)									
GLCM(D=1)	85.9	87.6	93.9	96.0	95.2	93.2	93.4	94.5	93.3
GLCM(D=2)	85.5	86.7	94.1	95.6	95.6	93.3	93.1	94.4	93.7
LBP	79.9	81.7	92.5	96.3	96.8	93.3	93.4	93.3	91.8
LTP	79.8	75.9	91.6	96.2	96.6	93.2	92.4	93.0	93.5
Tamura	86.9	87.0	95.0	96.0	95.1	92.8	92.0	94.2	93.1

explore the space of possibilities and performance. The KNN classifier was tested with different distance measuring methods (Euclidean, City block, and Cosine distance) and weighted KNN was also used to for classification.

It was observed that the cubic polynomial kernel SVMs performance was better than the other classifiers. The classification of gangue from limestone was 96.8% accurate by using colour features of H, S Cr and Cb and texture features of V and Y channel extracted using LBP. The classification results are shown in Table 1.

5.0 Conclusions

A vision-based ore sorting model based on analysis of colour and texture features is presented. Three different colour spaces were used for the analyzing of colour-texture features of limestone and associated gangue. Initially, the texture features were computed both between and within the colour bands of RGB colour spaces. Joint colour-texture features were extracted from HSV and YCbCr colour spaces using GLCM, LBP, LTP and Tamura methods. 10-fold cross-validation was used for evaluating the classifiers. The performance of SVM with cubic polynomial kernel was better with 96.8% accuracy as compared to the traditional pattern classifiers (linear and quadratic discriminant analysis) and modern classifiers KNN with different distance measuring methods (Euclidean, City block, and Cosine distance) and weighted KNN.

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(Continued on page 40)