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An Investigation of Lung Maturity Analysis through Kernelized Fuzzy Rough Set Feature Partitioning

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ABSTRACT

Background: An Investigation of Lung Maturity Analysis through kernelized Fuzzy Rough Set Feature Partitioning. **Objective:**This paper proposed a novel method to determine the maturity of fetal lung through kernelized fuzzy rough set feature partition. The fetal lung maturity test monitors the unborn baby's lungs, to check whether the baby can able to breathe on his/her own. The main objective of the proposed work is to find the discriminant feature extraction. Initially Contrast Limited Adaptive Histogram Equalization (CLAHE) method is proposed for preprocessing, to improve the local contrast of the lung image. After preprocessing, feature extraction is proposed to extract the textural features. It gives the information about the textural characteristics of the image. To obtain the approximation quality of the feature, Feature Partitioning is implemented with the help of kernelized fuzzy rough set. Finally Multinomial Bayesian classification is proposed to classify the ultrasonic images as mature and immature.The experimental results show that the proposed method dramatically reduces the dimensionality of original feature space. The discriminant feature set from a kernelized fuzzy rough set can be carried out in the reduced lower dimensional subspace, which improves the accuracy of the classification algorithm. **Results:** For experimentation of the proposed technique, the fetal lung image is obtained from normal pregnant women at intervals of 2 weeks from the gestational age of 24 to 38 weeks. Fig. 2 shows the echogram samples of the fetal. By using CLAHE method, preprocessing of fetal image is processed. After preprocessing, different types of texture features are extracted from the raw feature set. **Conclusion:**This paper proposes a novel method to identify the fetal lung maturity analysis by using kernelized fuzy rough set feature partitioning. In order to obtain the optimized result, processes like preprocessing, feature extraction, feature partitioning and classification is performed. The kernelized fuzzy rough sets are used to evaluate the features and to compute the memberships of samples to the lower and upper approximation of decision classes. The proposed system gives 100% of classification accuracy which is higher than that of existing systems.

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INTRODUCTION

FETAL lung maturity analysis is essential to identify the condition of fetal lung due to the immaturity of the fetal lung. It is a tedious method which consists of physiological, cellular and biological function. The degree of maturity of the lung is analyzed by biophysical and biochemical methods, which is obtained by needle puncture. If there is any complication present in the report, then treatment should be given before delivery.Data's are collected from pregnant women at intervals of two weeks from the gestational age of 24 to 38 weeks. Baby has to take oxygen from the mother, so if there is an insufficient of surfactant of alveoli, then the infant will have Respiratory Distress Syndrome(RDS). Prenatal Diagnosis (PD) helps in managing the remaining weeks of pregnancy. Many techniques are available for PD. Each of them should be applied at the specific time interval. Fetal lung maturity tests are achieved on amniotic fluid and they calculate fetal lung maturation either by quantifying components of pulmonary surfactant (e.g. Lecithin, phosphatidylglycerol, and lamellar bodies) or by measuring the surface active effects of the phospholipids in the surfactant.Test to assess fetal lung maturity are

- Lamellar body count
- Surfactant/albumin ratio
- Phosphatidylglycerol

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- Lecithin/sphingomyelin

Lamellar body count approach to the initial screening of amniotic fluid for the assessment of fetal lung maturity. It is characterized by resistive-pulse counting of the lamellar bodies, the surfactant containing of the lamellate structure that are secreted by type IIpneumocytes and are associated with pulmonary maturity. Surfactant/albumin ratio test is performed as a screening test for pregnancies requiring fetal maturity testing. In this method the positive predictive value is 45.3%; the negative predictive value is 97.4%.Phosphatidylglycerol (PG) test can be accomplished by thin-layer chromatography, which is cheaper and quicker. This PG identification is not usually affected by blood, meconium secretion. There is a high, falsely immature rate due to its late appearance in pregnancy.Lecithin/sphingomyelin plays a major role in fetal lung maturity analysis. L/S ratio is determined by thin-layer chromatography. This technique requires highly trained person, expensive and time consuming.

Current changes in clinical practice to minimize the need for identifying fetal lung maturity.More obstetricians are planning ultrasound examinations previously during pregnancy, thereby implementing gestational age more precisely. Ultrasound is a noninvasive method, it does not affect fetal and mother. The lung to liver ratio is calculated to analyze, whether the fetal lung is in mature state (reduces pulmonary risk) or immature (possible pulmonary risk) state. In this method, image of fetal thorax and abdomen are viewed by longitudinal and transverse section. The features used are fractional dimension, lacunarity and feature derived from the histogram of the images. To classify the fetal lung images, the following classification is proposed to identify mature or immature lung: nearest neighbor, k-nearest neighbor, modified k-nearest neighbor, multilayer perceptron, radial basis function network and support vector machines. The classification accuracy obtained for the testing set ranges from 73% to 96%. The existing methods increase the execution time and memory usage.

This paper proposes a fetal lung maturity analysis of a reduced set of features obtained from kernelised fuzzy rough set theory. In this method preprocessing technique is carried out by Contrast Limited Adaptive Histogram Equalization (CLAHE) method. The extracted features are of large dimension in nature. After preprocessing, feature extraction, feature partioningand classification are performed. This paper integrates kernel function with fuzzy rough set models. Fuzzy T- equivalence relations are helpful in fuzzy rough set based data test. The main objective of this paper is to find the discriminant features, to reduce the memory utilization for feature matrix and to improve the classification accuracy.

The rest of the paper is organized as follows. Section II presents a description about the previous research which is relevant to the analysis of fetal lung maturity analysis. Section III involves the detailed description about the proposed method. Section IV presents the benchmark results for the datasets. This paper concludes in Section V.

Related work:

This section deals with the works related to the fetal lung maturity analysis. *Rasheed, et al (*Rasheed, 2012*)* suggested that by measuring the lung growth in earlier stages of Gestational Age (GA) was helpful to prevent the infants from respiratory problems. Fetal thalamic echogenicity by ultrasound technique was used to measure the maturity level of the fetal lung. In this method, they measured the thalamus growth by measuring the biparietal diameter (diameter of the head), presence of amniotic fluid and placental changes. It was measured by linear ultrasound with convex transducer whose frequency level was 3.5 MHZ. If the thalamus echogenicity level was 86.53%, it means fetal lung was mature level, suppose it was 57.69%, then fetal lung was in an immature state.*Ghidini, et al (2011)* determined fetal lung measurement by Lecithin-Sphinomyelin ratio (L:S). If the L: S value was 2, it indicates the absence of Respiratory Distress Syndrome (RDS). If it was 1.5- 1.9, then the infant will have RDS.

Maeda (2013) suggested that in earlier days fetal lung growth was measured by the physical properties of amniotic fluid obtained by amniocentesis. But, amniocentesis may cause some risk to the fetus, so they followed Gray Level Histogram Width (GLHW). This method was based on the ratio of lung to liver intensities. *Chen, et al*[4] stated that ratio of antenatal ambroxol, dexamethasone(Dex) and betamethasone (Beta) present in the respiratory organ were used to predict RDS.*Schmid, et al (2011)* suggested smoking during pregnancy also affects the fetal lung growth. At present, ultrasound and Magnetic Resonance Image (MRI) were used for diagnosing the fetal lung. MRI technique was based on the basic of Fetal Lung Volume (FLV).

$\text{Fetal lung volume (mL)} = \exp(1.24722 + 0.08939 \times \text{gestational age in weeks})$. Antenatal corticosteroids were used to prevent respiratory distress syndrome. They had planned to prohibit cross over trials and cluster-randomized trials Finally, they stated that Dexamethasone reduced the risk of intraventricular hemorrhage.

Balassy, et al (2010) proposed Signal Intensity Ratio (SIR) and Lung Volume (LV) were used to calculate the fetal lung growth. Lung/ Liver Signal Intensity Ratio (LLSIR) was predicted by U test and finally compared with LV. *Allison, et al (2010)* evaluated the lung maturity analysis by Automatic Quantitative Ultrasound Analysis (AQUA). In this analysis, fetal thorax was viewed by manual delineated box mounted in the lung area. AQUA transformed the information into a set of descriptors. Genetic Algorithm (GA) extracts the descriptors and creates a model. This model distinguishes the mature and immature lung. This method gave robust feature to predict the TDx-FLM result. *Zamora (2013)* determined the relationship between the presence of hernia sac and fetal lung growth. Suppose if the mother had more amount of the sac. It indicated that she had liver herniation. It would affect the fetal lung growth.

Tsai, et al (2013) detected that Congenital Cystic Adenomatoid Malformation of the lung (CCAML) was the most common abrasion. Fetal CCAML was determined by three dimensional ultrasound method. *Simard, et al.(2010)* proposed Androgen Receptor (AR) mechanism which was used to predict the fetal lung maturity level. Type 2 and 517β-hydroxysteroiddehydrogenises (17βHSD) were focused in Androgen Receptor inactivation and synthesis. AR was detected in cytoplasm and nucleus. Present of AR would cause immature lung growth. *Silva, et al (2012)* proposed Antenatal stimulation of lung growth as an advanced method to treat congenital diaphragmatic hernia (CDH). It was classified by pulmonary hypoplasia, hypertension and the RAS components (Renin Angiotensis System) were constitutively expressed in the lung. Antenatal treatment improves the lung growth without affecting the mother and infant.

Azpurua, et al (2010) introduced acceleration/ejection time ratio in the fetal pulmonary artery to determine the fetal lung maturity level. In this method, pulmonary artery flow velocity waveform was compared with amino fluid. *Stranzinger, et al (2013)* proposed Computer tomographies (CT). Infants have low lung volume at alveolar stage, so it was difficult to view the lung image in this period. By CT process, the image was viewed clearly because CT technique has higher resolution comparing to all other technique. G. *Stichtenoth, et al (2013)* stated that treatment for lung maturity with exogenous pulmonary surfactant. Immature lung was treated with CPAP, conventional ventilation and surfactant. Captive Bubble surfactometer (CBS) gave surface activity. This surface activity was determined from the small volume aspirates of the upper airways of infant by using CBS. Finally, the result was compared with some clinical data.

Tsuda, et al (2012) determined the lung maturity analysis by Lamellar body count (LBC). These lamellar bodies were counted by platelet channel on the Sysmex. LBC cutoff value is $2.95\times10^4/\mu L$ concluded 91.5% sensitivity and 83.3% specificity for predicting RDS. *Oka, et al. (16)* suggested that the lung fluid was secreted by fetal lung. It was the major aspect of the measurement of fetal lung maturity analysis. This technique was based on the measurement of water content of the lung on the T2- weighted image. Measurement of Lung to Liver Signal Intensity Ratio (LLSIR) on T2 weighted images was calculated and then the relationship between LLSIR and percentage of respiratory distress syndrome was compared. *Kamath, et al (2011)* stated that infants who were born before 39 weeks of gestation had high rate of neonatal morbidities when compared with the infant born on or after 39 weeks of gestation.

Gary[18] highlighted that mothers who has type-1 Diabetes Mellitus (DM) and born before 39 weeks of gestation had a problem of fetal lung immaturity. *Maeda*[19] recommended Ultrasonic Doppler Actocardiogram (UDA) and GLHW tissue characterization techniques for identifying the fetal lung maturity. UDA was used to diagnose the Fetal Heart Rate (FHR), Feta movement signals and GLHW tissue characterization were identified by B mode apparatus. In this method, the behavior of placental tissue was characterized and grade 3 placenta was analyzed. *Moshiri, et al (2013)* determined the ratio of fetal lung to liver signal intensities by MRI technique. It was based on single –shot fast spin–echo sequence of the fetal chest and abdomen. In this method, Region Of Interest (ROI) of the fetal lung and liver was derived. Linear regression analysis was used to calculate the relationship between LLSIR in the ROI and fetal EGA (Estimated Gestation Age).

Proposed method:

This paper proposed a new method for the prediction of fetal lung maturity by means of the reduced feature set. The stages involved in the proposed method are shown below.

- ➢ Preprocessing
- ➢ Feature extraction
- Spatial Gray-Level Dependence Matrices
- Gray-Level Difference Matrix
- Laws' Textural Measures
- Fractal Dimension and Lacunarity
- Histogram-Based Features
- ➢ Feature Partitioning
- ➢ Prediction by Kernelised Bayesian

The preprocessing of the image is carried out by Contrast Limited Adaptive Histogram Equalization (CLAHE) method. After preprocessing, feature extraction is performed to extract different types of textural features. Finally, feature partitioning and prediction are performed.

A. ***Preprocessing:***

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a preprocessing method commonly used in medical imaging to improve the local contrast of the lung image. CLAHE differs from ordinary adaptive histogram equalization (AHE) in its contrast limiting. The contrast limiting procedure has to be applied for each neighborhood from which a transformation function is derived. The contrast amplification in the vicinity of a given pixel value is given by the slope of the transformation function, which is proportional to the slope of the Cumulative Distribution Function (CDF) and therefore the value of the histogram at that pixel value. This technique works on a small area in the given image. It improves every tile's contrast and the nearest tables and then they are integrated by bilinear interpolation. Along with the enhancement of the image, it bounds the slope for the gray level assignment scheme which results in limitation of saturation. CLAHE technique is easy to use, requires smaller computational requirement and greater improvement in the quality of the image.

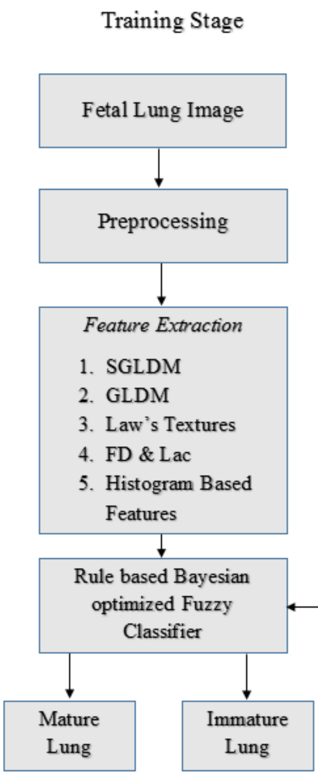

Fig. 1: Flow diagram.

B. *Feature Extraction:*

In working with image processing techniques, the image feature extraction phase is very consequential. The extraction of texture features provides the information about the textural characteristics of the image. The following methods are used to extract the textural features.

1) Spatial Gray-Level Dependence Matrices(SGLDMs):

SGLDMs are depend on the evaluation of second order joint conditional probability density functions, specified by $f(x, y|d, \theta)$.It is the probability that a pair of pixels isolated by a distance d at an angleθ have gray levels$x$and$y$. The angles are quantized to $45°$intervals. In the proposed method, five texture features are computed and it is shown below:

$$E = \sum_x \sum_y [R_\theta(x, y|d)]^2 \quad (1)$$

$$H = -\sum_x \sum_y \theta(x, y|d) \log R_\theta(x, y|d) \quad (2)$$

$$C = \frac{1}{\sigma_m \sigma_n} \sum_x \sum_y (x - \mu_m)(y - \mu_n) R_\theta(x, y|d) \quad (3)$$

$$I_n = \sum_x \sum_y (x - y)^2 R_\theta(x, y|d) \quad (4)$$

$$L = \sum_x \sum_y \frac{1}{1+(x-y)^2} R_\theta(x, y|d) \quad (5)$$

Where$\mu_m = \sum_x \sum_y R_\theta(x, y|d)$and $\sigma_m^2 = \sum_x (x - \mu_m)^2 \sum_y [R_\theta(x, y|d)]$. The overall values of $x \in (0, G - 1)$ and $y \in (0, G - 1)$ are carried out by these two summations. $R_\theta(x, y|d)$is the $(x, y)^{th}$ element of R_θ for a specified d, G is the number of gray levels in the image. $R_{\theta^\circ}(d) = P(x, y|d, \theta^\circ)$.

2) Gray-Level Difference Matrix(GLDM):

Let us assume $I(m, n)$ be the image intensity function. For any given displacement $\delta = (\Delta m, \Delta y)$, let $I_\delta(m, n) = |I(m, n) - I(m + \Delta m, n + \Delta n)|$ and $f'(i|\delta)$ be the probability density of $I_\delta(m, n)$. If there are G gray

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levels, this has the form of an G-dimensional vector whose i^{th} component is the probability that $I_\delta(m,n)$ will have value i. The value of $f'(i|\delta)$ is determined from the number of times $I_\delta(m,n)$ occurs for a given δ. Four possible forms of the vector δ are considered $(0,d),(-d,d),(d,0)$ and $(-d,-d)$. d is the interpixel distance. Five texture features are extracted from each of the density functions.

$Contrast: Con = \sum_i i^2 f'(i|\delta)$ (6)

$Mean = \sum_i i f'(i|\delta)$ (7)

$Entropy: E = \sum_i f'(i|\delta)\log(f'(i|\delta))$ (8)

$InverseDifferenceMoment: IDM = \sum_i f'(i|\delta)/(i^2+1)$ (9)

$AngularSecondMoment: ASM = \sum_i [f'(i|\delta)]^2$ (10)

3) Laws' Textural Measures:

Laws textural energy measures are obtained from three vectors such as local averaging, edge detection and spot detection. Each vector have three length $L3 = \{1,2,1\}, E3 = \{-1,0,1\}$ and $S3 = \{-1,2,-1\}$. Three vectorsare obtained by these vectors are convolved with themselves or with one another. Each vectors have length five: $L5 = \{1,4,6,4,1\}, E5 = \{-1,-2,0,2,1\}$ and $S5 = \{-1,0,-2,0,-1\}$. The masks used in this proposed analysis are $L5^T E5$ and $L5^T S5$. With each image, these masks were convolvedand the entropy of the resulting image was determined.

4) Fractal Dimension and Lacunarity:

Based on the concepts of multiresolution image analysis and fractional Brownian motion model (fBMM), the fractal dimension (FD) is computed. The roughness and granularity of the fractal surface is characterized by the FD and lacunarity. The intensity difference vector (IDV) is defined for an $R \times R$ image I is $IDV = [id(1), id(2), \ldots\ldots id(m)]$, where $id(h)$ is the average of the complete intensity difference of all pixel pairs with vertical or horizontal distance h and m is the maximum possible scale. The $id(h)$ is computed as

$$id(h) = \frac{1}{2R(R-h-1)}\left(\sum_{x=0}^{R-1}\sum_{y=0}^{R-h-1}|I(x,y)-I(x,y+h)| + \sum_{x=0}^{R-h-1}\sum_{y=0}^{R-1}|I(x,y)-I(x+h,y)|\right) \quad (11)$$

$F_d = 3 - B$, where F_d is the fractional dimension and the value of B is calculated by using least squares linear regression to evaluate the slope of the curve of $id(h)$ versus h in log-log scale. In a given fractal set D, let $P(r)$ be the probability that there are r points within a box of size S, centered about an arbitrary point of D. $\sum_{r=1}^{N} P(r) = 1$, where N is the number of possible points within the box. The LAC is defined as

$$\wedge = (R_2 - R^2)/R^2 \quad (12)$$

Where $R = \sum_{r=1}^{N} rP(r)$ and $R_2 = \sum_{r=1}^{N} r^2 P(r)$. (13)

5) Histogram-Based Features:

Mean, variance (VAR), coefficient of variation (CV), kurtosis, skewness and second moment (SM) are calculated by the histogram based features.

C. Feature Partitioning:

To estimatethe approximation quality and approximation abilities of the features, the existing measures in classical rough sets are extended based on the models of kernelized fuzzy rough sets. The model of kernel based fuzzy rough sets can be used to calculate the membership degrees of a sample to the lower approximation and upper approximation of its decision. It is also used to compute the memberships of a sample to the upper approximations of other classes. Hence, the approximation quality and approximation accuracy of a set is defined.Fuzzy T-equivalence relations are very useful to fuzzy rough set-based data analysis.

To calculate the fuzzy T-equivalence relations between samplekernel functions are employed in this paper, thus creating fuzzy information granules in the approximation space. Consequently fuzzy granules are used to estimate the classification based on the concepts of fuzzy lower and upper approximations.

1) Kernel Fuzzy Rough Sets:

It has been revealed that any kernel $K: UxU \to [0,1], K(x,x) = 1\ \forall x \in X$, is T_{cos}-transitive,where $T_{cos}(a,b) = \max(ab - \sqrt{1-a^2}\sqrt{1-b^2}, 0)$. Fora given non-empty set U and a kernel function K being Kernels $K(x,y)$ are obtained such that they execute reflexivity, symmetry $K(x,y) = k(y,x)$ and T_{cos}-transitivity. These kernels are used to estimate the degree to which objects r and s are related to every feature. In kernelised fuzzy rough set lower and upper approximations are defined by:

S-kernel fuzzy lower approximation operator:

$$\underline{K_S}X(x) = \inf_{y\in U} S(N(k(x,y)), X(y)) \quad (14)$$

θ-kernel fuzzy lower approximation operator:

$$\underline{K_\theta}X(x) = \inf_{y\in U} \theta(k(x,y), X(y)) \quad (15)$$

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T-kernel fuzzy upper approximation operator

$$\overline{K_T}X(x) = \sup_{y\in U} T(K(x,y), X(y)) \tag{16}$$

σ-kernel fuzzy upper approximation operator

$$\overline{K_\sigma}X(x) = \sup_{y\in U} \sigma(N(K(x,y)), X(y)) \tag{17}$$

2) Approximating classification with kernel:

Classification is one of the most significant problems in pattern recognition and machine learning. Consider the fuzzy lower approximation of classification with kernel functions. The classification can be expressed as < L,C,Z>, where L is the nonempty and finite set of samples, C is the set of features characterizing the classification, Z is the class attribute which divides the samples into subset $\{d_1, d_2, \dots . d_k\}$. For $\forall x \in U$,

$$d_i(x) = \begin{cases} 0, & x \notin d_i \\ 1, & x \in d_i \end{cases} \tag{18}$$

The kernel function K is used to calculate the fuzzy similarity relation between samples. The decision subsets with the fuzzy granules induced by the kernel is approximated. The algorithms for calculating the fuzzy lower and upper approximations for a given kernel function is

$$\underline{K_S}d_i(x) = \inf_{y\notin d_i} (1 - k(x,y)) \tag{19}$$

$$\underline{K_\theta}d_i(x) = \inf_{y\notin d_i} (\sqrt{1 - k^2(x,y)}) \tag{20}$$

$$\overline{K_T}d_i(x) = \sup_{y\in d_i} K(x,y) \tag{21}$$

$$\overline{K_\sigma}d_i(x) = \sup_{y\in d_i} (1 - \sqrt{1 - k^2(x,y)}) \tag{22}$$

D. ***Prediction by kernelized Bayesian:***

Multinomial Bayesian classification is proposed to classify the ultrasonic images as mature and immature.Based on a Probabilistic Model Specification (PMS)any kind of abnormalities can be classified. Features that define data instances are conditionally independent given the classification hypothesis.Multivariate multinomial distribution for discrete data that fit assumes each individual feature follows a multinomial modelwithin a class. The parameters for a feature include the probabilities of all possible values that the corresponding feature can take. Bayes rule is stated as follows,

$$P\left(\frac{h}{d}\right) = \frac{P\left(\frac{d}{h}\right)P(h)}{P(d)} \tag{23}$$

Where d=data, h=hypothesis. Rearranging the above equation,

$$P\left(\frac{h}{d}\right) * P(d) = P\left(\frac{d}{h}\right) * P(h) \tag{24}$$

$P(d,h) = P(d,h)$have the same joint probability on both sides.Training phase of the Multinomial Bayesian classifier evaluates the parameters of a probability distribution using the training samples. The posterior probability of unseen test sample is evaluated by prediction phase of the classifier. After that the test sample is distinguished based on the greatest posterior probability. With the help of classification accuracy analysis, accuracy rate is obtained.

Result analysis:

For experimentation of the proposed technique, the fetal lung image is obtained from normal pregnant women at intervals of 2 weeks from the gestational age of 24 to 38 weeks. Fig. 2 shows the echogram samples of the fetal. By using CLAHE method, preprocessing of fetal image is processed. After preprocessing, different types of texture features are extracted from the raw feature set.

Fig. 2: Fetal Lung Image.

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By examining the extracted features of various fetal lungs, classification is done by multinomial Bayesian classification.The multivariate multinomial distribution is appropriate for categorical features. The Naïve Bayes classifier evaluates a separate set of probabilities for the set of obtained feature levels in every class. Whereas the naïve classifier is appropriate when features are independent of one another within a class.

The accuracy rate is obtained from the validation of the classification performance analysis. The validation is performed with the accuracy parameters such as correct rate, error rate, last correct rate, last error rate, inconclusive rate, classified rate, sensitivity, specificity, positive/negative predictive value, positive/negative likelihood and prevalence. The textural features are shown in the Table I. This involves in the image classification process under mature and immature categories.

Table I: Textural Feature Analysis.

S.No	Parameters	Value
1	Correct rate	1
2	Error rate	0
3	Last correct rate	1
4	Last error rate	0
5	Inconclusive rate	0
6	Classified rate	1
7	Sensitivity	1
8	Specificity	1
9	Positive predictive value	1
10	Negative predictive value	1
11	Positive likelihood	NaN
12	Negative likelihood	0
13	Prevalence	0.5000

The confusion matrix gives the confirmation for the classifier performance along with the obtained parameters. The accuracy obtained in the classification methodology is 100%. The confusion matrix is shown in the Fig.3.

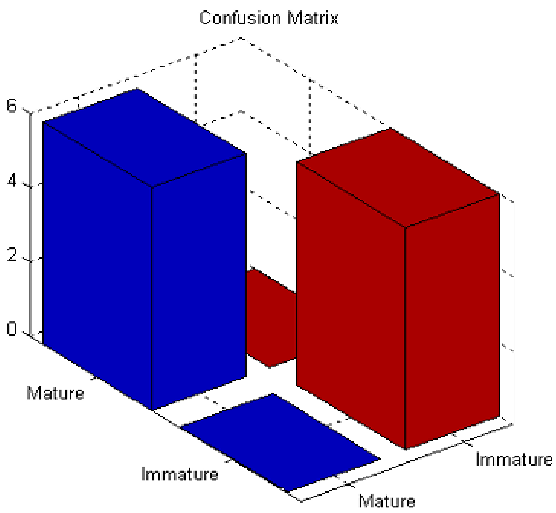

Fig. 3: Confusion Matrix.

The Fig.4 shows theamount of mature and immature fetal lung imagescategorized using multinomial Bayesian classification. The proposed method reduces the execution time of the classification algorithm. The memory usage is also reduced by obtaining the discriminant feature set from kernelised fuzzy rough set theory.

Table II: Classification accuracy analysis

Classifiers	Classification Accuracy in percentage
Nearest neighbor	88.93
K-nearest neighbor	77.53
Modified K-nearest Neighbor	88.13
Multilayer Perceptron	80.5
Radial basis function network	80.93
Support vector machine	82.9
Multinomial Bayesian	100

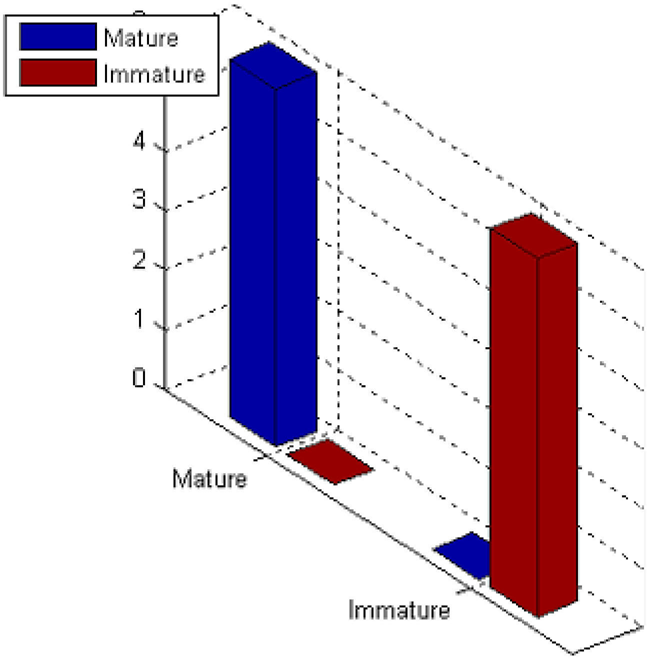

Fig. 4: Performance Analysis.

The classification accuracy of the proposed method is compared with the existing methods are shown in the Table II. The accuracy rate achieved by the proposed Multinomial Bayesian classification provides 100%.

Conclusion:

This paper proposes a novel method to identify the fetal lung maturity analysis by using kernelized fuzy rough set feature partitioning.In order to obtain the optimized result, processeslike preprocessing,feature extraction, feature partitioning and classification is performed. The kernelized fuzzy rough sets are used to evaluate the features and to compute the memberships of samples to the lower and upper approximation of decision classes. The proposed system gives100%of classification accuracy which is higher than that of existing systems.

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