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Cervic cancer classification using quantum fuzzy set

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Abstract

In this sophisticated world living with CIN cervic cancer is much jeopardy. Cancer is a stochastic (random) process. So, in that CIN in initial stage is not jeopardy. It is totally because of hazardous malign cells. Using its modality in image is selected in existing system only automated classification depends on input image. But in proposed methodology the innovative alludes the jeopardy of CIN cancer is found using the size of /area of nucleus or cytoplasm. This proposed methodology was developed with an algorithm to find CIN area/size. This research work establishes a Cervic Cancer Classification Using Contour Based on Area of Nucleolus and Cytoplasm in Cells (CBANC) which classifies noise spread images into any one of five phases. A similarity measure produces 90% efficiency in proposed system as par with inefficient existing system which fetches us 50%. By pragmatic application it is proved that CBANC with fuzzy is better than Baye's. This can be accomplished by removing well distinct consistency features and choosing preeminent classifier. Proposed work can extend with 3D input images for future research. It produces mightiest parameter shape and intensity which is very essential for 3D approach. The inference of proposed system can extend the latest classifier engines for more accuracy. It can easily predict more than 90% accuracy will be there. And also derive cancer growing and after therapy for cancer shrinking algorithm will be used for 2D or 3D CIN cancer classification. The outcomes of the proposed methodology CBANC shows that better when compared to the existing methodology like Bayes. It can be implemented in the real world environments of the medical field.

1. Introduction

Nowadays it is ubiquitous that cancer is because of malign cells. This malign cell fetches cancer will be identified and cured by chemotherapy, radiation or radio surgery. Cells develop abnormally and multiply in endometrial cancer. Abnormal cells can invade adjacent tissues as well as other human organs. This tissue of a cervical margin, which would be located at the base of the cervix, is where ovarian cancer first develops. With irregular cell phases, the contaminated uterus cells proliferate and replicate [1]. Women experiencing precancerous cervical carcinoma do not experience any indications till the disease progresses to metastatic carcinoma and extends to certain other body systems because it is a slow-growing infection. The cancer has a protracted which was before phase, making an early detection totally treatable and avoidable. This condition is the most prevalent kind of cancer in Indian women between the ages of 15 to 44. According to the most current GLOBOCAN 2018 findings from the "International Agency for Research on Cancer," the five major female malignancies in India are pulmonary, chest, cervical, ovarian, and oral mucosa malignancies. The anticipated prevalence and fatality rates among those top five malignancies in Indian women of all ages. Cervical uterus cancer is currently the second most common form amongst top five, followed by breast

cancer. Statistics from GLOBOCAN 2018 show that there were roughly 96,000 new instances of ovarian cancer reported in India, down from 123,000 in 2012 and 134,000 in 2008 [2]. Approximately 60,000 people died from cancer in 2018, down from 73,000 in 2008.

Because of the awareness raised by efficient screening programmes, as well as the value of basic evaluation and treatment programmes employed for abnormalities identification, the prevalence and mortality levels have dramatically decreased. According GLOBOCAN 2020's most recent figures, [3] ovarian cancer and pancreatic cancer are the two most common cancers affecting women. According to Fig. 3, the incidence of melanoma has decreased from 28% to 23% and that of ovarian cancer has decreased from 17% to 9%. The rate of cervical cancer amongst Indian women has significantly decreased. A regular pap test called the Papanicolau Smear was called by Dr. Papanicolau. It is among the often utilised conventional diagnostic tests that aids in identifying abnormalities in cervical tissue [4].

The diagnostic technique aids in the earlier detection of abnormalities in the premalignant phase. Precancerous cervical death and recurrence rates were decreased in developed countries thanks to regular and required testing. Cancer currently poses a severe threat to women in poor nations because to its high incidence and death rates, as well as a deficit of resources, inadequate information, and its effects. Automatic analysis tools for Pap smears have some drawbacks, such as limited capability (inability to correctly determine the sample carrying the disease), doubts about cost efficiency, and inability to identify cases of early irregularities. The "U.S. Preventive Services Task Force (USPSTF)" declared in 2003 that there was insufficient support for using iot technology on a regular basis [5].

The "National Coordinating Centre for Health Technology Assessment" came to the conclusion that effectiveness, effect, and price of automated processes are all still unsatisfactory in 2005. According to "Obstetrics and Gynecology of India's" "Screening for Cervical Cancer: an overview" from 2006, multiple researches are need to assess this technique before it can be incorporated into a screening programme. [6] Significant limitation and expensive equipment cost, according to a 2011 Health Technology Evaluation journal article titled "Manual Assessing vs Automatic Reading in Cytology (MAVARIC)," stated there was no rationale for the adoption of testing protocols. The physical examination of cell pictures is time-consuming and arduous since physicians must examine each picture on a contaminated slide under the microscopy in order to diagnose a cancer [7]. The testing of the overall population necessitates the examination of a large amount of samples, that requires months and calls for skilled staff. Diagnostic imaging technological improvements have increased the quality of medical images, which has improved benefits to an early diagnosis of illnesses. Competitive computer-assisted diagnostic technologies like PapNet and AutpPap300 was created to streamline the testing procedures, however most of these products have drawbacks such as high false positive percentages, doubts about their expenditure, and an inability to identify low-grade irregularities [8]. Despite the existence of advanced automation methods for smear testing, developing and middle-income nations having high rates of cervix cancer incidence and mortality do not effectively deploy automated tools due to their high cost and upkeep requirements. [9] Therefore, the creation of an affordable and efficient computerized screening instrument has grown into a significant research topic that aids physicians in the quick examination and correct diagnosis of specimens.

In this research, a Cervic Cancer Classification Using Contour Based on Area of Nucleolus and Cytoplasm in Cells (CBANC) identification in female patients. The related methods for cervical cancer diagnosis are presented in Section 2, and the proposed methodology is expounded in Section 3. The results and discussion are covered in Section 4, and the work is concluded in Section 5.

2. Related works

The simplest form of the organism, the cellular, is responsible for each of the functions that make up life. The research of lymphocytes, their physiological changes, morphology, and internal compartments, as well as their relationships with the environment, cell growth, and death of cells, is known as cytogenetic or molecular genetics. Cytopathology is a field of research that focuses on diagnosing cellular illnesses by the observation of cellular changes in regards to size, structure, colour, and roughness [10]. The cytoplasmic, the membranes, and the nuclei are indeed the three primary components of a cell. The nucleus, that serves as the cell's central nervous system, contains genetic traits and deoxyribonucleic acid (DNA) in the form of chromatins, an ensures proper a web within the core. An artificial neural classification method in [11] to identify and separate the malignancy location in pictures of the cervical vertebrae. To enhance the precision of cancer identification, the authors combined their suggested method with a technology known region expanding vectorization. A strategy was put forth to find the aberrant cervical areas in female patients. Using a Computer Aided Detection (CAD) method, the researchers scanned the individuals' cervix areas using biopsy pictures. With the use of several computational intelligence techniques, this computer-assisted methodology raises the cervix medical diagnostic system's generalization ability. In comparison to objective reality pictures, the researchers' tumour classification technique was 91% and their sensitivities was 86% [12].

Pap smear cell detection was employed in [13] to identify uterine cancer in female patients. The power and textural characteristics were extracted from the cervix picture and employed by the Support Vector Machine (SVM) classifier to classify the cervix images. The categorization accuracy for Pap smear cells that the researchers attained was 96.12%. This method's primary flaw is that it simply works with high-definition photographs. The precompiled cervix image was further

analyzed using a histogram approach to obtain colour characteristics. The Nave Bayes classifier was used to evaluate and categorise these retrieved colour histogram characteristics. An technique for extracting features was used to classify the cervix pictures [14]. Using both the pathological and normal categories, the scientists retrieved texture and gradients information. Sub fold classification was used to learn and classify these characteristics. For the purpose of detecting uterine cancer, a feature extraction-based classification algorithm. From of the cervix picture, the researchers identified textural and energy configuration characteristics, which were then learned using the quasi-supervised learning (QSL) technique. The authors used a labelled and unlabeled dataset with known and unidentified cervix pictures to evaluate their suggested technique. For the collection of 132 cervix pictures, the authors implemented 88% True Positive Rate (TPR) and 19% False Positive Rate (FPR) both in pathological and normal categories [15].

An method for applying SVM classifiers to identify uterine cancer. The researchers first collected textural features from histopathology pictures, and after training and classifying these characteristics using an SVM classifier. For the identification of ovarian cancer, the researchers' classification performance was 92.8%. On biopsies cell pictures, The cervical tumor categorization technique. The cervix picture was first deconstructed by the scientists using the wavelet transforms, and from the deconstructed parameters, characteristics like as energy and enthalpy were then retrieved [16]. The cell pictures were categorised as either elbow dysplasia or malignant cancer using the KNN classifier to identify the retrieved characteristics.

Cervical cancer is commonly originated in endo-cervix, ecto-cervix and conversion region. Here cervical cancer is to be identified by counting the number of malign cells and classify according to feature [17, 18]. Figure 1 displays the cervical cancer processing. So it follow is,

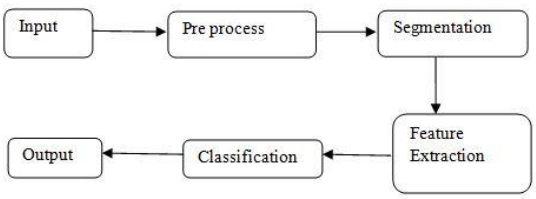

Figure 1. Cervical cancer Processing.

In this above method preprocess is filtering only. Next segmentation stage by feature extraction with very strongest sub parameter contrast. Hence the flow starts with input the cancer image and it was preprocessed by the transformation fourier which is the mightiest then threshold the transformed image so that inversed transform which makes the input image completely filtered. Even we can prescribe curvelet transform. Then according to GLCM the mightiest parameter texture which has 17 sub parameter among them contrast is the outstanding. So futures were extracted through different parameters in segmentation. Then the input is cancer image was classified according to the area of the nucleus and cytoplasm. Then initially among thousands images were trained. Even the input can be from pubmed [19]. It is trained so that classification is very easy.

A scheme for the recognition of cytoplasm and core commencing Thin Prep images. The arithmetical vigorous curves were utilized in segmentation implementation. In such technique, localization of compartment substance was completed in stumpy resolution and margin recognition of cytoplasm and core were completed in elevated resolution [20].

The computerized technique to identify the core in noise spread images. Using morphological psychotherapy, the nucleus centroids are identified and by pertains space reliant rule and classification tactic on resulted centroids, the objectionable relics were unconcerned from the cell [21].

Countless automatic [22] and semiautomatic [23] tactic have been projected to identify nucleus curve of cervical cells on the noise spread images and to classify the regular from anomalous dysplasia cells. A tactic [24] for cell nucleus recognition in noise spread images was projected. The positions of the aspirant nucleus centroids in the representation were identified with morphological psychotherapy and that are distinguished auxiliary integrated a priori understanding concerning the perimeter of every nucleus.

3. Proposed methodology

The proposed CBANC categorization scheme classify the noise spread images into one of five phases, (a) exterior squamous, (b) columnar, (c) soft dysplasia, (d) sensible dysplasia, and (e) cruel dysplasia. Fig. a, b, c, d, e shows trial single unit images first row symbolizes three phases of regular image and subsequent row symbolizes two phases of cruel type and fuzzy logic. In the projected classification, we used SVM technique to classify the noise spread images [25].

Regarding modality so many types which are (i)X-ray (Digital or ordinary)(ii)MRI (Magnetic resonance imaging) (iii)CT-scan (Computed Tomography) Tomo means slices which compute x axis slices is meant for dividing input image which is in 3D also.

According to Fourier transform the mathematical lemma in equation-(1) is,

$$F[x(t)] = \int_{-\alpha}^{\alpha} x(t)e^{-jwt}\,dt \qquad (1)$$

It is referred any mathematical function can be represented in sine and cosine form. The above is continuous Fourier transform.

The Discrete Fourier Transform (DFT) which changes a finite sequence equally spaced samples of a function into a same length sequence of equally spaced samples of discrete fourier transform which is a complex valued function of frequency in equation-(2) is below,

$$X(f)=\{\sum x(n).\delta(t-nT)\} \qquad (2)$$

Where as in inverse DFT in equation-(3) is,

$$\sum x(n).\delta(t-nT)\text{=invese of F(X (f))} \quad (3)$$

Among the fourier transform the anchored attribute is convolution. For a sequence of convolution in one domain multiplication in another domain. So the mathematical lemma of convolution in equation-(4) is,

$$x*y\text{= inverse DFT } [DFT(x)DFT(y)] \quad (4)$$

Hence first fourier transform it then multiply it then inverse it. But in wavelet transform the lemma is continuous in equation-(5) is,

$$T[f(\gamma)] = \int_{-\alpha}^{\alpha} f(t)\varphi_r * (r)dt \quad (5)$$

By wavelet transforms responses scaling and translation i.e. multiple resolution in equation-(6) so,

$$\varphi_{\mu s}(+) = \frac{1}{\sqrt{5}}\varphi(\frac{t-\mu}{s}) \quad (6)$$

While in discrete wavelet transform in equation-(7)

$$\varphi(x) = \sum_{n}(h_{\varphi})(n)\sqrt{2\varphi}(2x-y) \quad (7)$$

The discrete Fourier and wavelet transform for digital computer used in preprocessing. Neural network means neuron they are arranged in layers by layers. Figure 2 displays artificial neuron. It is mainly used in cancer recognition. Recognition is also one type of classification say yes or no. Here x_1, x_2….x_n are inputs.W_1, W_2…,W_n are weights. The output equation-(8) is,

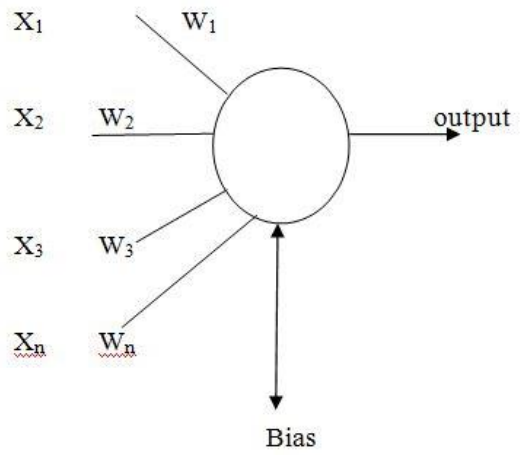

Figure 2. Artificial Neuron.

$$\text{Y=output =}\sum w * x + bias \quad (8)$$

The neural network used in identification. By Baye's theorem [1] according to conditional probability the mathematical lemma in equation-(9) is,

$$P(A/B) = \frac{P(B/A)\,P(A)}{P(B)}. \quad (9)$$

It was classified grade1, grade2, grsde3 and grade 4. The SVM is support vector machine it is efficient classifier engine e which is binary classifier which iterates to multiple classification.

There are three parameters are used in identification and classification the three main parameters texture, colour and shape. Identification is also one type of classification yes or no. The omnipotent texture (external parameter) has seventeen sub parameters. Statistical GLCM is (gray_leavel co-occurrence matrix) is a statistical method of testing (outer surface texture) in that the following mathematical lemma.

3.1. Contrast

In the contrast lemma the value i-j increases the value increases exponentially. By GLCM the statistical properties allude mean of contrast and standard deviation. Of contrast and how it is strayed by standard deviation. It is purely like ex-or gates. When the input is different output is one. So the mathematical lemma in equation-(10) is,

$$Contast = \sum_{1=0}^{N-1}\sum_{j-0}^{N-1}(i-j)(i-1)(g(i,j)) \quad (10)$$

3.2. Homogeneity

By GLCM the statistical property are alluded mean of correlation and standard deviation of correlation. So consider the mathematical lemma of energy again and again. In the above parameters we have fifteen sub parameters are there. In that five sub parameters are analyses. Their pragmatic approach fetches us impeccable solutions. For that reason the energy, contrast are analyzed again.

Contrast behaved ex-or gate principle. When the inputs are different output is one. It plays vital role in change detection. Its deviated, So the contrast its inversely proportional homogeneity in equation-(11),

$$Hf5 = \sum_i \sum_j = \frac{1}{1+(i-j)(i-j)}\ \text{p (i,j)} \quad (11)$$

Larger window with little contract of homogeneity. By GLCM method the standard deviation value mansion how long it's deviated, so the contrast it's inversely proportional homogeneity.

3.3. Energy

The Energy of cell is displayed in equation-(12)

$$\text{Energy=}\ \sum_{i=0}^{g-1}\ \sum_{j=0}^{g-1}(p(i,j))^2 \quad (12)$$

3.4. Entropy

The Entropy of cell is displayed in equation-(13)

$$\text{Entropy=}\ \sum_{i,j=0}^{n-1} P_{i,j}(-lnP_{i,j}) \quad (13)$$

The energy and entropy are how they are related explained in next coming topics which are needed.

The above mentioned mathematical lemma is not only limited. In correlation instead of two functions we

can say a function and lag of same function is called correlation. That to auto correlation. If both are different functions then cross correlation occurs. This ex-or gate mechanism plays vital role.

3.5. Correlation

The correlation is displayed in equation-(14)

$$Hf_3 = (\sum_i \sum_f (i,j)\, p(i,j) - u_x u_y) / \sigma x\, \sigma y \quad (14)$$

Hence in GLCM after refer, confer and infer found that the above mentioned sub parameters are used in texture easily detect cancer identification and classification. Figure 3 shows the input images.

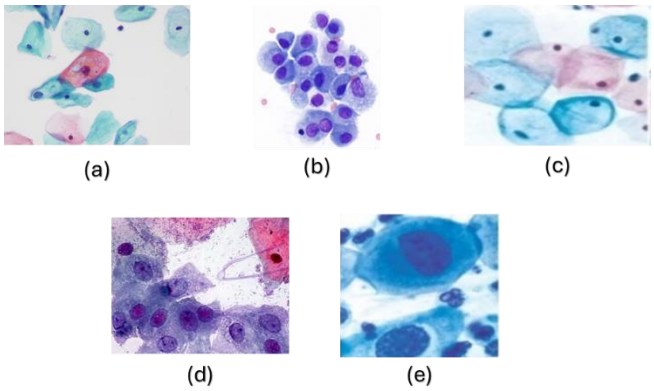

Figure 3. Input image (a), Input image (b), Input image (c), Input image (d), Input image (e).

While in fabulous diagram in proposed methodology the flow of the input image is converted to gray level. Then it is fed into transformation for pre processing can wavelet or fourier it. The figure 4 displays the flow gives acumen and pragmatic innovative approach. Hence reduce the following diagram as follows.

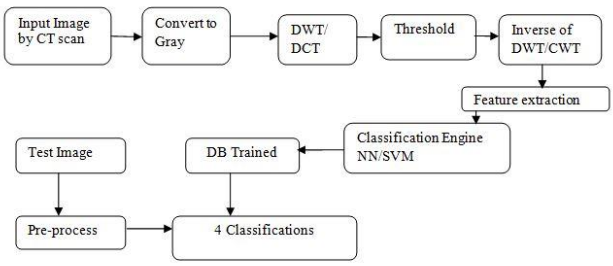

Figure 4 Proposed Flow Diagram.

The input pragmatic mechanism of different age group is 20 to 30, 30 to 40, 40 to 50, 50 to 60 and above for ladies CIN images were taken. These images feature extracted called and trend to different age group of 200 to 1000 images.

The input testing image is fed then which will be matched with databases of trained according to conditional probability is also called Bayesian classifier engine is available in neural network. Another classifier engine was SVM (Support Vector Machine) which is for ladies of the age group 20 to 30, 30 to 40, 40 to 50, 50 to 60 and above. It classifies 20-30/no for benign cell single nuclear cell area <single cytoplasm cell area. For malign cell it reverses above cases.

Algorithm CBANC
To calculate its area of nucleus and cytoplasm
/* let i is initial count */
Begin
do
Step1:preprocessed;
input image(i+1)
temp <-0
0<-S_N, S_C, i,j;
Step2: feature extracted;
Random select cell of I input image
step 3: S_N →the size of nucleus (inner contour)
step 4 :S_C→The size of (outer contour) by contour.
S C/A = (S_N / (S_N - S_C)) %
Step 5: S C/A classified
(i) 0-25% no cancer
(ii) 25% - 50% initial stage
(iii) 50% -75% matured
(iv) 75% < totally matured
i <-i+1;
j <- j+1;
}
(while i<100, j<100)

}
End

Table 1. Fuzzy Logic and Possibility Value.

Input image	Inner contour	Outer contour	Possibility
S(0)	Sh(0)	N(0)	VF(-1)
S(0)	Sh(0)	E(1)	F(0)
S(0)	Sh(0)	R(2)	LI(1)
S(0)	M(1)	N(0)	F(0)
S(0)	M(1)	E(1)	LI(1)
S(0)	M(1)	R(2)	I(2)
S(0)	R(2)	N(0)	LI(1)
S(0)	R(2)	E(1)	I(2)
S(0)	R(2)	R(2)	HI(3)
Me(1)	Sh(0)	N(0)	F(0)
Me(1)	Sh(0)	E(1)	LI(1)
Me(1)	Sh(0)	R(2)	I(2)
Me(1)	M(1)	N(0)	LI(1)
Me(1)	M(1)	E(1)	I(2)
Me(1)	M(1)	R(2)	HI(3)
Me(1)	R(2)	N(0)	I(2)
Me(1)	R(2)	E(1)	HI(3)
Me(1)	R(2)	R(2)	Sturdy(4)
L(2)	Sh(0)	N(0)	LI(1)
L(2)	Sh(0)	E(1)	I(2)
L(2)	Sh(0)	R(2)	HI(3)
L(2)	M(1)	N(0)	I(2)
L(2)	M(1)	E(1)	HI(3)
L(2)	M(1)	R(2)	St(4)
L(2)	R(2)	N(0)	HI(3)
L(2)	R(2)	E(1)	St(4)
L(2)	R(2)	R(2)	VS(5)

SVMs are a set of associated administer education technique that investigate data and utilized for categorization and deterioration psychotherapy to classify prototypes. Normally SVM obtains set of data as inputs, and guesstimates the input, to facilitate an element of that class; a non-probabilistic binary linear classifier is created. The SVM instruction replica guesses whether an innovative investigation representation

belongs to one class or based on training illustrations. SVM categorization occupies detection of substance confidentially associated to the identified phases. SVM generates a hyper-flat surface among two groups of data for categorization. The fuzzy logic and possibility outcomes are displayed in Table 1.

S-Small, Me-Medium, L-large, Sh-Short, M- Modest, R- Regular, N- Nearer, E- Enough R- Remote, VF- Very Feeble, F- Feeble, LI- Lower Intermediate, I- Intermediate, HI- Higher Intermediate, St- Sturdy, VS- Very Sturdy.

4. Results and Discussion

According to classifier engines CBANC and bayes. While result analysis for the age group 20-30 years. Bayes says cancer is available whereas CBANC negated so it is referred, conferred and inferred that at initial ages no cancer will be found. So CBANC classification is success.

Table 2 Displays the data for it age group 20 -30 years.

Sl.No	0-25	25-50	50-75	above 75
Bayes	40	32	18	10
CBANC	45	40	10	05

The bar graph elicits x-axis cancer state Y-axis number of patient. Figure 4 displays the cancer cells indentified According to age group 20-30 bar graph is,

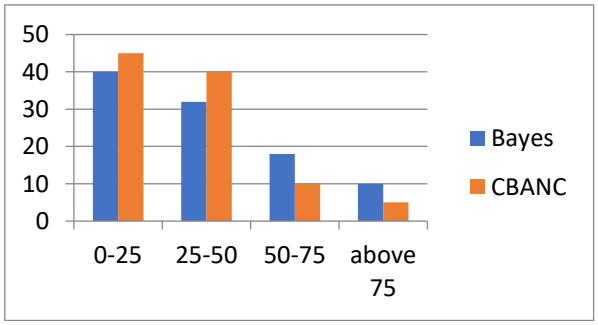

Figure 3. Age group among 20-30.

Table 3. Displays the data for it age group 30 – 40 years.

SL.No	0-25	25-50	50-75	above 75
Bayes	30	40	15	15
CBANC	15	10	10	65

For the age group between 30 to 40 both the classifier engines (bayes, CBANC) predict equally. Figure 5 displays the cancer cells indentified according to age group 30-40 bar graph is,

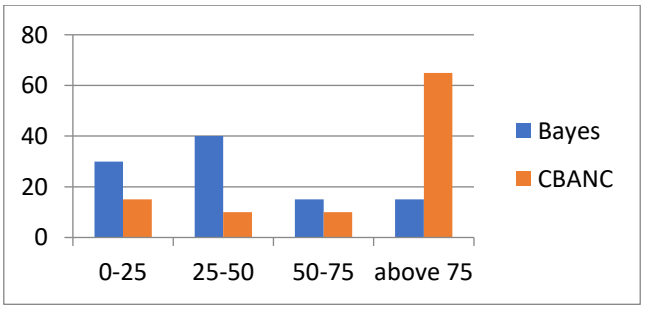

Figure 5. Age group 30 – 40 years.

Table 4. Displays the data for it age group 40 – 50 years.

SL.No	0-25	25-50	50-75	above 75
Bayes	50	25	20	05
CBANC	30	12	18	40

For the age group between 40 to 50 slightly CBANC upholds the Bayes. Figure 6 displays the cancer cells indentified according to age group 40-50 bar graph is,

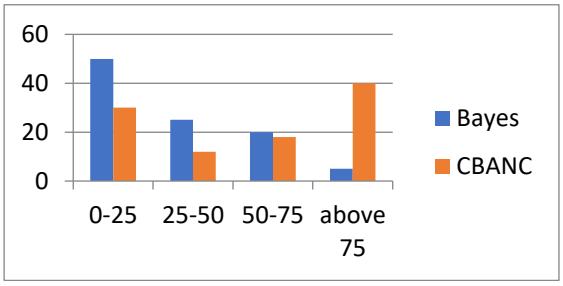

Figure 6 Age group 40 – 50 years.

Table 5. Displays the data for it age group 50 – 60 years.

SL.No	0-25	25-50	50-75	above 75
Bayes	60	20	10	10
CBANC	10	12	17	61

For the age group between 50 to 60 better classifications for CBANC than Bayes. Figure 7 displays the cancer cells indentified according to age group 50-60 bar graph is,

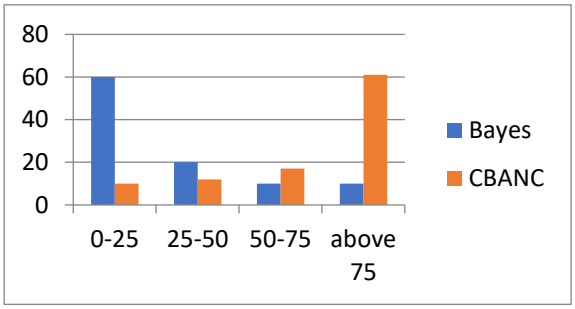

Figure 7 Age group 50 – 60 years.

Table 6. Displays data for age group above 60 years.

SL.No	0-25	25-50	50-75	above 75
Bayes	60	20	20	0
CBANC	0	15	35	50

For the age group above 60 is CBANC anchored its prediction. Figure 8 displays the cancer cells indentified according to age group above 60 bar graph is

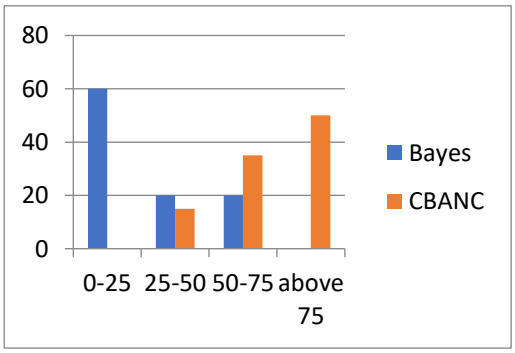

Figure 8. Age group Above 60 years.

Table 7. Displays data for age group combining 20 to 60.

SL.No	0 to 25	25 to 50	50 to 75	above 75
Bayes		127	83	40
CBANC	100	89	90	221
Original	50	50	100	200

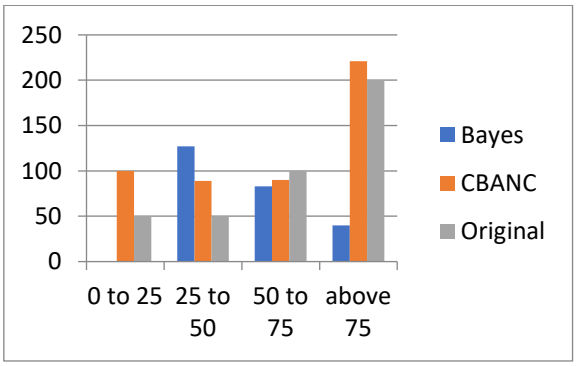

Figure 9 Age group combining 20 – 60 years.

Figure 9 displays the cancer cells indentified according by combining different age group levels 20 - 30,30-40,40-50,50-60 and above 60.It confers CBANC classifier is almost equal to original cancer than Baye's. So CBANC is referred, conferred and inferred that CBANC produces 90% accuracy than existing method.

So in pie-chart the above can be drawn as among all years produces better output compared to the existing techniques. Figure 10 displays the cancer cells indentified among entire people.

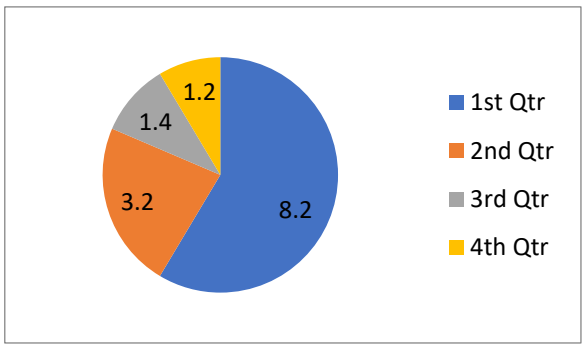

Figure 10 Entire age grouped People.

5. Conclusion

This research work gives excellent proficient diagnosis by meticulous and dexrotrous classifying engine called CBANC. The extension of project is images can be extended to 3D with different modality images. For examples instead of CT scan MRI, PET produces mightiest parameters in shape and intensity for 3D accuracy above mentioned modalities is used for future research. And also, we can derive cancer growing and after therapy for cancer shrinking algorithm will be used for 2D or 3D CIN cancer classification.

Author contributions

Rajesh Dennison: Conceptualization, Methodology, Software, and Validation **Giji Kiruba DASEBENEZER:** Conceptualization, Methodology and Software. **Ramesh Dennison:** Investigation, Methodology and Software.

Conflicts of interest

The authors declare no conflicts of interest.

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