

## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

# Prediction of Skin Cancer Using Morphological Neural Network Analysis

M.Ishwarya, J.Sudha, M.E.,(Ph.D.),

M.E. Computer Science and Engineering, Department of Computer Science and Engineering, A.V.C. College of Engineering, Mannampandal, Mayiladuthurai, Tamil Nadu, India

Associate Professor, Department of Computer Science and Engineering, A.V.C. College of Engineering, Mannampandal, Mayiladuthurai, Tamil Nadu, India

**ABSTRACT:** In image processing domain, the complex task to analyze and rectify is cancer estimation and prediction. Compare to tumor estimations, Cancer estimations are more complex because these are purely cell based paradigms and visually not clear to analyze; especially this system focus on skin cancer and its strategies. Morphological Neural Network with Image Pruning Scheme is introduced to efficiently classify the cancer cells and mark out the affected region also and its accuracy can be predicted more efficiently. In past systems extracted texture and color features used a BoF model to code these features to classify skin-lesions. It is hard to compute skin cells. The features were extracted from image patches, in order to better cope with incomplete skin-lesions. But in this system, MNN is used to evaluate skin lesions and it gives high accuracy.

**KEYWORDS:** MNN, Morphological Neural Network, Skin Cancer, ROI.

## I. INTRODUCTION

Recently, cancer patients are increasing due to following factors: lifestyle, smoking tobacco, alcohol usage, diet, physical activity, environmental change, sun and other types of radiation, viruses and so on. The most common type cancer includes skin cancer. Unusual swellings of cells for skin can be the skin cancer. There are four kinds of skin cancers: Actinic Keratoses (AK), Basal cell carcinoma (BCC), Squamous cell carcinoma (SCC), and Melanoma. Early diagnosis of the cancer helps to treat it successfully. The late diagnosis of the cancer causes the cancer spread to other nearby organs, and cannot be treat. There are numerous publications are composed in detecting, segmenting, and classifying skin cancers employing different computer vision, machine learning, image processing, MNN, and classification techniques. Esteva et al. developed the skin cancer classification using MNN. Hitoshi et al. presented a quite automatic system for the classification of the melanomas. While Anas et al. composed the melanoma classification by four kinds classification, Almansour et al. demonstrated a classification method for melanoma using the k-means clustering and Support Vector Machine (SVM). Abbas et al., and Capdehourat et al. composed skin lesions, cancers, and dermoscopy image classification methods using AdaBoost MC, separately. Giotis et al., and Ruiz et al. developed decision support systems utilizing image processing and neural network algorithms by lesion texture, color, visual diagnostic attributes, and affected area, degree of damage for the melanoma, respectively. Also, Isasi et al. presented an automatic melanomas diagnosis system. The cutaneous melanoma is diagnosed by Blum et al. Kiran et al. developed an Android application for the melanoma classification. As a subfield of the deep neural network, MNNs has

# International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

recently achieved great success in machine learning and computer vision. In 2012, Krizhevsky et al. presented a novel method using MNN to classify large (1.2 million high-resolution) images in the ImageNet LSVRC-2010 at the Neural Information Processing Systems Conference. It is a first-mover advantage of the MNN in computer vision. The AlexNet model has some benefits, i.e., preeminent implementation, few training parameters and extreme validity. Also, the major superiority is the network pre-trained on the ImageNet dataset. Additionally, the input images are clearly recognizable from anything in the ImageNet network. A majority of the image is black because the image is being viewed through an endoscope.

The actual content of the image is generally tissue, with the tool being the contrasting object from the background. This poses a trickier problem given that the majority of the images contain a repetitive background with some type of surgical tool which tends to bear the same color and relative shape. Cireşan et al. applied multi-column deep neural networks for image classification. A number of systems are presented in image classification using MNNs, such as Chen et al., Wei et al., Li et al., Zeiler et al., Srdjan et al., and Cireşan et al. Also, Sermanet et al. classified digits of realworld house numbers using MNNs. Several publications are demonstrated in multiclass classification. Amornsamankul et al. presented combining hybrid approaches, i.e., Complementary Neural Networks (CMTNN) and Error-Correcting Output Codes (ECOC) in solution multiclass classification problem. Bagheri et al. composed ECOC in multiclass classification. Yan et al. analyzed a performance in ECOC SVMs, and also applied ECOC SVM in remote sensing image classification. Liu et al. developed a method in speech recognition using SVM and ECOC. This system addresses the demand for an intelligent and rapid classification system of the skin cancer using contemporary highly-efficient MNN. In this system, we mainly focus on the task of the classifying skin cancer using ECOC SVM with existing, and pre-trained AlexNet MNN. This system is arranged as follows: the mentioned summary describes the MNN. The following details present objectives and newly proposed methodology in detail. The following summary shows experimental outputs using proposed algorithm.

## II. SYSTEM IMPLEMENTATION

### A. IMAGE ACQUISITION

The main purpose of this image acquisition module is to acquire the image and convert as Matrix format. Dataset collection of skin cancer images is stored in the database. This is the process known as image acquisition. The image acquisition process consists of three steps; energy reflected from the object of interest, an optical system which focuses the energy and finally a sensor which measures the amount of energy. The first stage of any vision system is the image acquisition stage. After the image has been obtained, various methods of processing can be applied to the image to perform the many different vision tasks required today. However, if the image has not been acquired satisfactorily then the intended tasks may not be achievable. Image acquisition in image processing can be broadly defined as the action of retrieving an image from some source, usually a hardware-based source, so it can be passed through whatever processes need to occur afterward. Performing image acquisition in image processing is always the first step in the workflow sequence because, without an image, no processing is possible. The image that is acquired is completely unprocessed and is the result of whatever hardware was used to generate it, which can be very important in some fields to have a consistent baseline from which to work. One of the ultimate goals of this process is to have a source of input that operates within such controlled and measured guidelines that the same image can, if necessary, be nearly perfectly reproduced under the same conditions so anomalous factors are easier to locate and eliminate

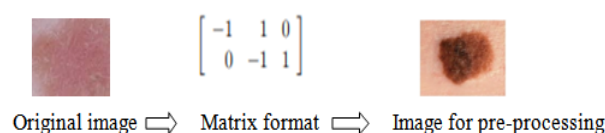


Fig.1 Image acquisition

## International Journal of Innovative Research in Science, Engineering and Technology

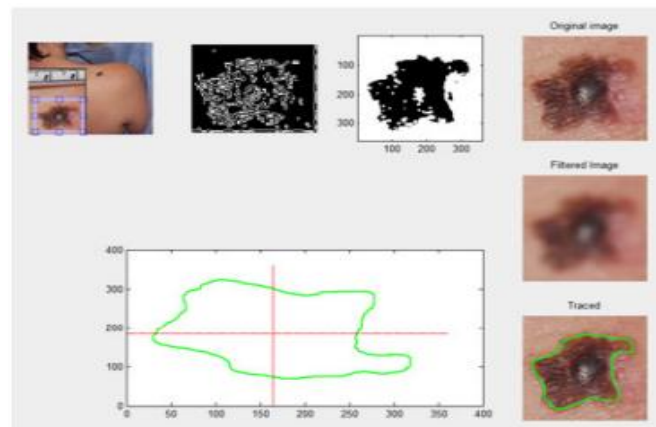
(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

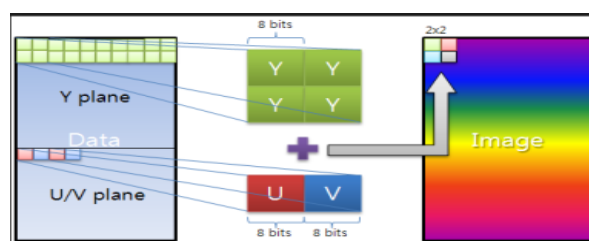
### B. IMAGE PREPROCESSING

The main necessity of this image preprocessing module is to enhance image quality. Image pre-processing can significantly increase the reliability of an optical inspection. Several filter operations which intensify or reduce certain image details enable an easier or faster evaluation. The following are the examples of image pre-processing method Normalization, Edge filters, Soft focus, selective focus, User-specific filter, Static/dynamic Binarization, Image plane separation and Binning. This modules comprises many internal works include: Includes several functions for image processing, Contrast increase by static or dynamic Binarization, look-up tables or image plane separation, resolution reduction via binning and conversion of color images to gray value images. The most complex descriptor family is the polygon shape based descriptors, which potentially require several image pre-processing steps to isolate the polygon structure and shapes in the image for measurement. Polygon shape description pipelines may involve everything from image enhancements to structural morphology and segmentation techniques. Setting up the pre-processing for polygon feature shape extraction typically involves more work than any other method, since thresholds and segmentation require fine-tuning to achieve good results. Also note that polygon shape descriptors are not local patterns but, rather, larger regional structures with features spanning many teens and even hundreds of pixels, so the processing can be more intensive as well.



**Fig.2 Image Preprocessing**

### C. YUV Conversion



**Fig.3 YUV conversion**

Y'UV is computed from RGB as follows:

$$Y' = WRR + WGG + WBB = 0.299R + 0.587G + 0.114B,$$

$$B - Y'$$

## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

$$U = U_{max} (1 - WB) \sim 0.492 (B - Y')$$

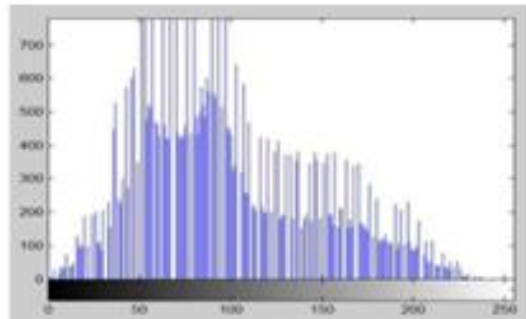
$$R - Y' V = V_{max} (1 - WR) \sim 0.877 (R - Y')$$

The resulting ranges of  $Y'$ ,  $U$ , and  $V$  respectively are  $[0, 1]$ ,  $[-U_{max}, U_{max}]$ , and  $[-V_{max}, V_{max}]$ .

### D. NOISE REMOVAL- MEDIAN FILTER AND CONTRAST CORRECTION

Median filtering is similar to using an averaging filter, in that each output pixel is set to an average of the pixel values in the neighborhood of the corresponding input pixel. However, with median filtering, the value of an output pixel is determined by the median of the neighborhood pixels, rather than the mean. The median is much less sensitive than the mean to extreme values (called outliers). Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image. Median Filter is a simple and powerful non-linear filter which is based order statistics. It is easy to implement method of smoothing images. Median filter is used for reducing the amount of intensity variation between one pixel and the other pixel. In this filter, do not replace the pixel value of image with the mean of all neighboring pixel values, replaces it with the median value.

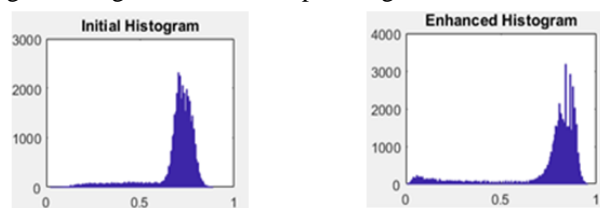
The contrast correction algorithm analyzes and/or corrects the brightness and contrast of 8 and 24-bit images. The analysis and correction phases can be used separately or together. The Quality setting controls how finely the image is sampled, and will also impact how sensitive the adaptive correction method is to local changes in contrast.



**Fig. 4 Sample histogram image**

### E. Histogram equalization

Histogram equalization is used to enhance contrast. It is not necessary that contrast will always be increase in this. There may be some cases where histogram equalization can be worse. In that cases the contrast is decreased. Let's start histogram equalization by taking this image below as a simple image.



(a) Initial image

(b) Enhanced image

**Fig.5 Histogram equalization of images**

## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

### F. IMAGE BINARIZATION

Binarization is the process of converting a pixel image to a binary image. The main contribution of this module is to Convert the gray image into binary and remove the unwanted contents of skin. The images were firstly divided into normal and abnormal. Based on the fact that abnormal cases involve masses and micro calcifications. This procedure was performed four times repeatedly for each level of decomposition, from level 2 to level 5. For each level, features extracted using the reduction procedure were utilized. Binary images may contain numerous imperfections. In particular, the binary regions produced by simple thresholding are distorted by noise and texture. These techniques can be extended to grayscale images. The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image.

Binarization generally involves two steps including determination of a gray threshold according to some objective criteria and assigning each pixel to one class of background or foreground. If the pixels intensity is greater than the determined threshold then it belongs to foreground class and otherwise to the background. The main problem in binarization is the choice of thresholding technique. Several thresholding algorithms have been investigated and proposed to define the optimal threshold value. The thresholding algorithms can be categorized into six classes: histogram shape-based methods, clustering-based methods, entropybased methods, object attribute-based methods, the spatial methods and local methods based on the local characteristics of each pixel. Among these classes, many thresholding algorithms are based on a minimum variance. Otsu's thresholding technique is a classification-based method which searches for the the threshold that minimizes the intra-class variance. Otsu's thresholding method is used for automatic binarization level decision, based on the shape of the histogram and also used for skin cancer identification. Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either falls in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum.

### G. ROI SELECTION AND SEGMENTATION

Image preprocessing techniques are essential for discovering the noise removal, and quality improvement of the image. Preprocessing steps are very significant to focus the identification of abnormalities without unnecessary influence from background of the image. For this study, the first phase of preprocessing entailed two procedures; noise elimination and image contrast enhancement. The second phase involves segmentation, which is executed to remove the background area (high intensity rectangular label, tape artifact, and noise). The third deals with the application of phase reduction and global gray level thresholding to extract ROI. A major issue in such an application is the automated robust detection of a region (ROI) in which a strong signal can be expected (e.g., usually the forehead or the cheek). To reduce the effect of image noise and intensity variations due to skin's repetitive texture and hair, an image is first low-pass filtered before being segmented.



Fig.6 Segmentation of skin lesion

## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

### H. FEATURE EXTRACTION USING MNN

The main motto of this feature extraction module is to extract the important data's from the image. This is the statistical feature and geometric like mean, brightness, skewness, kurtosis, area, perimeter. The function of feature extraction is to obtain new variables from the matrix of the image in order to create distinct classes. The feature extraction procedure involves the use of the wavelet decomposition process. These features are then classified in the next stage. Features extraction comprises five processing steps as illustrated as below, by which the features in the system are extracted from the wavelet coefficients. After getting these features we need to classify with trained data's.

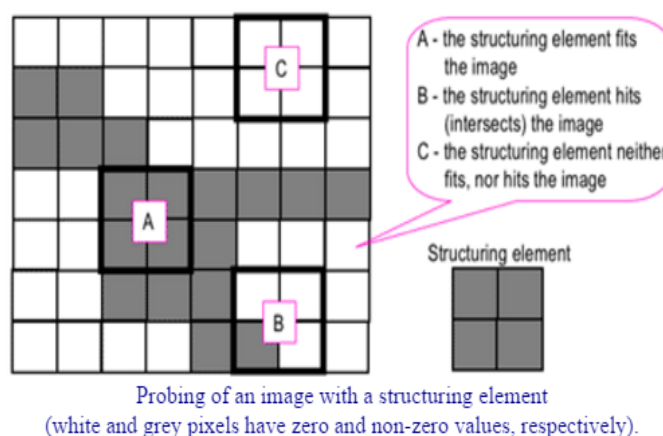


Fig.7 Morphological Analysis

A Morphological Neural Network (MNN) is a computational model developed based on the configuration and functions of biological neural networks. Information transmitted through the network influences the structure of the MNN since a neural network evolves or learns based on the input and output. The field is referred to with several names that include connectionism, parallel distributed, processing, neuro-computing, natural intelligent system, and machine learning algorithm. MNN is an organized system of basic processing elements, nodes or units, whose functions are to some extent derived from the animal neuron. The processing ability of the network is controlled by the inter unit connection strengths, or weights, achieved via adaptation to, or learning from, a set of training patterns. The most essential elements of MNNs are modeled after the configuration of the human skin.

### III. LITERATURE SURVEY

#### Body Screening for Skin Cancer: five-year prospective experience - S. Swensen, et al, 2010 [1]

**Purpose:** To report results of a 5-year prospective low-dose helical skin computed tomographic study of a cohort at high risk for Skin Cancer.

**Materials and Methods:** After informed written consent was obtained, 1520 individuals were enrolled. Protocol was approved by institutional review board and National Cancer Institute and was compliant with Health Insurance Portability and Accountability Act, or HIPAA. Participants were aged 50 years and older and had smoked for more than 20 pack-years. Participants underwent five annual (one initial and four subsequent) CT examinations. A significant downward shift was evaluated in non-small cell Skin Cancers detected initially from advanced stage down to stage I by using a one-sided binomial test of proportions. Poisson regression and Fisher exact tests were used for comparisons with Mayo skin Project.

**Results:** In 788 (52%) men and 732 (48%) women, 61% (927 of 1520) were current smokers, and 39% were former smokers. After five annual CT examinations, 3356 uncalcified skin nodules were identified in 1118 (74%) participants. Sixty-eight Skin Cancers were diagnosed (31 initial, 34 subsequent, three interval cancers) in 66 participants. Twenty-



## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

eight subsequent cases of non-small cell cancers were detected, of which 17 (61%; 95% confidence interval: 41%, 79%) were stage I Cancers. Diameter of cancers detected subsequently was 5-50 mm (mean, 14.4 mm; median, 10.0 mm). Analysis for a more than 50% shift in proportion of stage I non-small cell cancer detection did not show statistical significance. Forty-eight participants died of various causes since enrollment. Skin Cancer mortality rate for incidence portion of trial was 1.6 per 1000 person-years.

**Conclusion:** Body Scanning allows detection of early-stage Skin Cancers. Benign nodule detection rate is high. Results suggest no stage shift.

### Computed tomography screening and Skin Cancer outcomes - P. Bach, et al., 2007 [2]

**Purpose:** The main purpose is to screening and monitoring the Skin Cancer outcomes.

**Materials and Methods:** Screening using low-dose computed tomography (CT) represents an exciting new development in the struggle to improve outcomes for people with Skin Cancer. Randomised controlled evidence demonstrating a 20% relative Skin Cancer mortality benefit has led to endorsement of screening by several expert bodies in the US and funding by healthcare providers. Despite this pivotal result, many questions remain regarding technical and logistical aspects of screening, cost-effectiveness and generalizability to other settings. This review discusses the rationale behind screening, the results of on-going trials, potential harms of screening and current knowledge gaps.

**Results:** One of the most important issues confronting those who wish to consider implementation of LDCT screening in high-risk populations is the problem of the high rate of positive examinations, primarily pulmonary nodules.

**Conclusion:** This review discusses the rationale behind screening, the results of on-going trials, and potential harms of screening and current knowledge gaps.

### Screening for Skin Cancer with low-dose computed tomography: a systematic review to update the U.S. Preventive Services Task Force Recommendation - L. Humphrey, et al., 2013 [3]

**Background:** Skin Cancer is the leading cause of cancer-related death in the United States. However, persons with early Skin Cancer have lower Skin Cancer-related mortality than those with extensive disease, suggesting early detection and treatment of Skin Cancer might be beneficial. Low-dose computed tomography (LDCT) and skin x-ray (CXR) have been studied for early screening, with several new studies reporting results since the last review.

**Purpose:** To update the 2004 review of screening for Skin Cancer for the U.S. Preventive Services Task Force.

**Data Sources:** MEDLINE (2000 to 2012), Cochrane Central Register of Controlled Trials and Cochrane Database of Systematic Reviews (through fourth quarter 2012), Scopus, and reference lists.

**Data Extraction:** Details about participants, study design, analysis, followup, and results were abstracted; study quality was rated using established criteria, where applicable.

**Data Synthesis (Results):** Four trials reported the effectiveness of screening with LDCT for Skin Cancer in patients with personal smoking exposure: one large good-quality trial reported screening was associated with reduced Skin Cancer and all-cause mortality reductions of 20 percent (95% CI, 6.8 to 27.6) and 6.7 percent (95% CI, 1.2 to 13.6), respectively. Three small European trials (two fair- and one poor-quality) showed no benefit of screening. When the three good- or fair-quality trials were combined in random effects meta-analysis, the relative risk of Skin Cancer mortality was 0.81 (95% CI, 0.72 to 0.91). One trial evaluated CXR screening in over 150,000 participants from the general population and reported no benefit of screening in this group or in a subset with personal tobacco smoke exposure. The reported sensitivity of LDCT for detecting Skin Cancer ranged from 80 to 100 percent and specificity from 28 to 100 percent in six studies; each study varied in its reporting method. The harms associated with LDCT screening included radiation exposure ranging from 0.61 to 1.5 mSv per scan, some degree of overdiagnosis of Skin Cancer that varied by study, and a high rate of false-positive examinations, which were typically resolved with further imaging. Most patients with positive results who underwent an invasive procedure were diagnosed with Skin Cancer. Smoking cessation was not significantly impacted by screening, although individuals with positive or indeterminate screens showed a trend toward reduced smoking or sustained abstinence. Patients with positive or indeterminate scans had some evidence of short-term increases in anxiety and distress but not long-term in the five studies evaluating this; patients with negative scans had a reduction in distress. Finally, no trials comparing treatment of stage I non-small cell Skin Cancer (NSCLC) with no treatment have been conducted. However, survival associated with surgical resection

## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

was evaluated in 11 studies of mostly symptomatic and unselected patients that have shown 5-year survival rates in the 71 to 90 percent range for stage IA NSCLC and 42 to 75 percent for stage IB NSCLC and that surgical resection is the U.S. standard of care. Harms of treatment of stage I NSCLC were poorly reported and ranged among the studies that reported them.

**Limitations:** Three trials were underpowered and of too short of duration to reach conclusions on effectiveness of screening. Over diagnosis is an important harm of screening but its magnitude is uncertain. No studies of LDCT have reported results in women or minority populations.

**Conclusions:** Good evidence shows LDCT can significantly reduce mortality from Skin Cancer. However, there are significant harms associated with screening that must be balanced with the benefits. More efforts to reduce false-positive examinations are of paramount importance and smoking cessation remains the most important approach to reducing Skin Cancer mortality.

**Prognostic implications of cell cycle, apoptosis, and angiogenesis biomarkers in non-small cell Skin Cancer: a review - Singhal S1, Vachani A, Antin-Ozerkis D, 2012 [5] Purpose:** The main purpose is to identify the cell cycle affection over cancer attack patients.

**Materials and Methods:** Skin Cancer is the leading cause of cancer death in the U.S. with survival restricted to a subset of those patients able to undergo surgical resection. However, even with surgery, recurrence rates range from 30% to 60%, depending on the pathologic stage. With the advent of partially effective, but potentially toxic adjuvant chemotherapy, it has become increasingly important to discover biomarkers that will identify those patients who have the highest likelihood of recurrence and who thus might benefit most from adjuvant chemotherapy. Hundreds of papers have appeared over the past several decades proposing a variety of molecular markers or proteins that may have prognostic significance in non-small cell Skin Cancer. This review analyzes the largest and most rigorous of these studies with the aim of compiling the most important prognostic markers in early stage non-small cell Skin Cancer. In this review, we focused on biomarkers primarily involved in one of three major pathways: cell cycle regulation, apoptosis, and angiogenesis. Although no single marker has yet been shown to be perfect in predicting patient outcome, a profile based on the best of these markers may prove useful in directing patient therapy.

**Conclusion:** This review analyzes the largest and most rigorous of these studies with the aim of compiling the most important prognostic markers in early stage non-small cell Skin Cancer. In this review, we focused on biomarkers primarily involved in one of three major pathways: cell cycle regulation, apoptosis, and angiogenesis. Although no single marker has yet been shown to be perfect in predicting patient outcome, a profile based on the best of these markers may prove useful in directing patient therapy.

**Screening for epidermal growth factor receptor mutations in Skin Cancer - R. Rosell, et al., 2012 [8]**

**Background:** Activating mutations in the epidermal growth factor receptor gene (EGFR) confer hypersensitivity to the tyrosine kinase inhibitors gefitinib and erlotinib in patients with advanced non-small-cell Skin Cancer. We evaluated the feasibility of large-scale screening for EGFR mutations in such patients and analyzed the association between the mutations and the outcome of erlotinib treatment.

**Materials and Methods:** From April 2005 through November 2008, Skin Cancers from 2105 patients in 129 institutions in Spain were screened for EGFR mutations. The analysis was performed in a central laboratory. Patients with Cancers carrying EGFR mutations were eligible for erlotinib treatment.

**Results:** EGFR mutations were found in 350 of 2105 patients (16.6%). Mutations were more frequent in women (69.7%), in patients who had never smoked (66.6%), and in those with adenocarcinomas (80.9%) ( $P < 0.001$  for all comparisons). The mutations were deletions in exon 19 (62.2%) and L858R (37.8%). Median progression-free survival and overall survival for 217 patients who received erlotinib were 14 months and 27 months, respectively. The adjusted hazard ratios for the duration of progression-free survival were 2.94 for men ( $P < 0.001$ ); 1.92 for the presence of the L858R mutation, as compared with a deletion in exon 19 ( $P = 0.02$ ); and 1.68 for the presence of the L858R mutation in paired serum DNA, as compared with the absence of the mutation ( $P = 0.02$ ). The most common adverse events were mild rashes and diarrhea; grade 3 cutaneous toxic effects were recorded in 16 patients (7.4%) and grade 3 diarrhea in 8 patients (3.7%).



# International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

**Conclusion:** Large-scale screening of patients with Skin Cancer for EGFR mutations is feasible and can have a role in decisions about treatment.

## IV. SYSTEM ANALYSIS

### A. Existing System

In the past system, CNN can be used, the researchers face lots of struggle in the development of a unified approach that can be applied to all types of medical images and applications such as skin cancer estimation and tumor analysis. Even, the selection of an appropriate technique for a particular kind of medical image is a difficult problem. Thus, there is no universal accepted method for medical image segmentation process. So, it remains a challenging problem in image processing industry and computer vision fields. Therefore, researchers/developers decide to work out the result for cancer cell estimation and prediction accuracies.

### Disadvantages

- Compare to Tumor analysis, Cancer analysis are complex, so lots of accuracy oriented issues occurs.
- Accuracy levels of other classification algorithms such as FCM, SVM produces less than or equal to 95% of accuracy over processing.
- Probabilistic model and time consumption is high because of large number of iterations.

### B. Proposed System

The feature extraction stage entails five steps: wavelet decomposition, wavelet coefficient extraction, normalization, energy computation, and coefficient reduction. Lastly, the classification stage involves the combinatorial use of Morphological Image Processing and Artificial Neural Network, called “Morphological Neural Network with Image Pruning”, which is used to classify skin tissue into normal and abnormal. Patients with high-risk factors or symptoms or predisposed to specific diseases or illness, could be selected to see a specialist for more treatment. Utilizing the technology particularly Artificial Intelligence (AI) techniques in medical applications could lower the cost, time involved, human proficiency and medical inaccuracies. For all our proposed approach aims to provide the complete solution to the medical image processing strategy with the help skin cancer estimation and prediction scenarios.

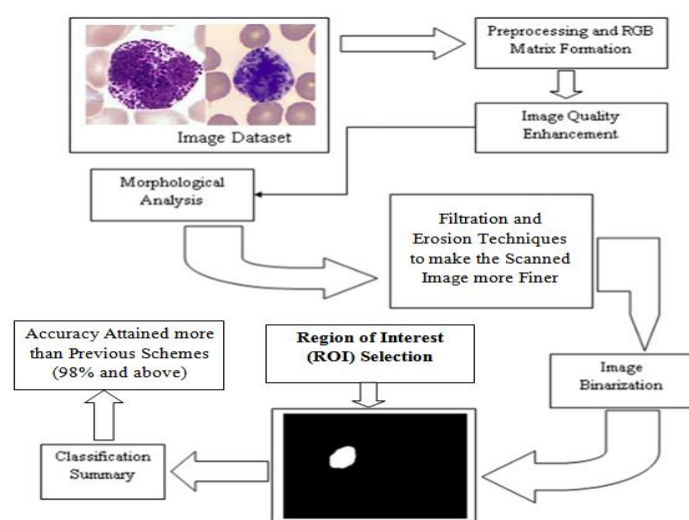


Fig.8 Proposed System Architecture

# International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

## Advantages

- Edge based and Region based Cell organization process gives more accuracy over predictions.
- Resulting speed is more because of low number of iterations, so performance is good.
- Classification is done via Morphological Neural Network, so the resulting accuracy is equal to 98%.

## V. RESULTS AND DISCUSSION

In this section, we provided the simulated results of entire project with its practical proofs. The following figure illustrates the Binarized Image View of the input image.

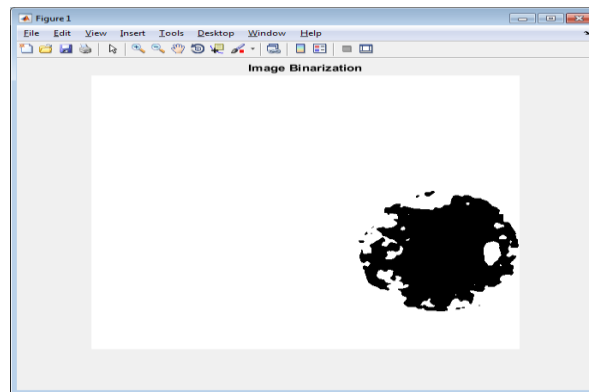


Fig. 9 Binary Conversion

The following figure illustrates the Segmentation view of the proposed system.

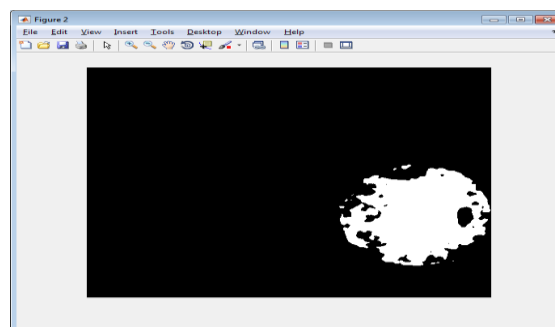


Fig.10 Image Segmentation

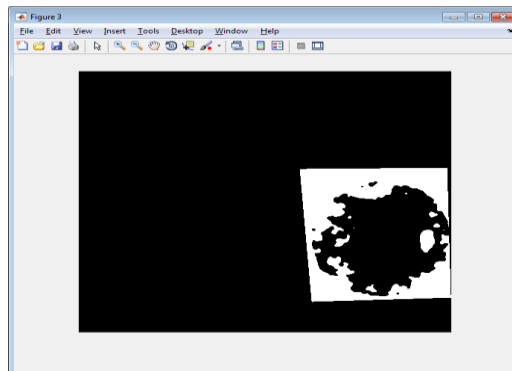
The following figure illustrates the ROI Selection view of the proposed system.

# International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

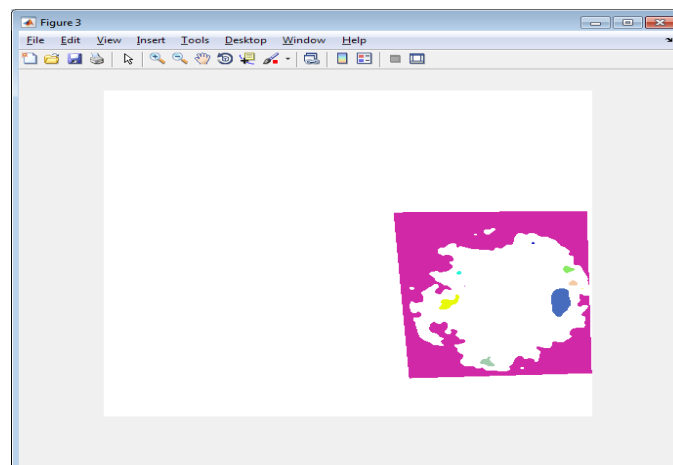
Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019



**Fig.11 ROI Selection**

The following figure illustrates the Feature Extraction view of the proposed system.



**Fig.12 Feature Extraction**

The following figure illustrates the Resulting Classification view of the proposed system.

# International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

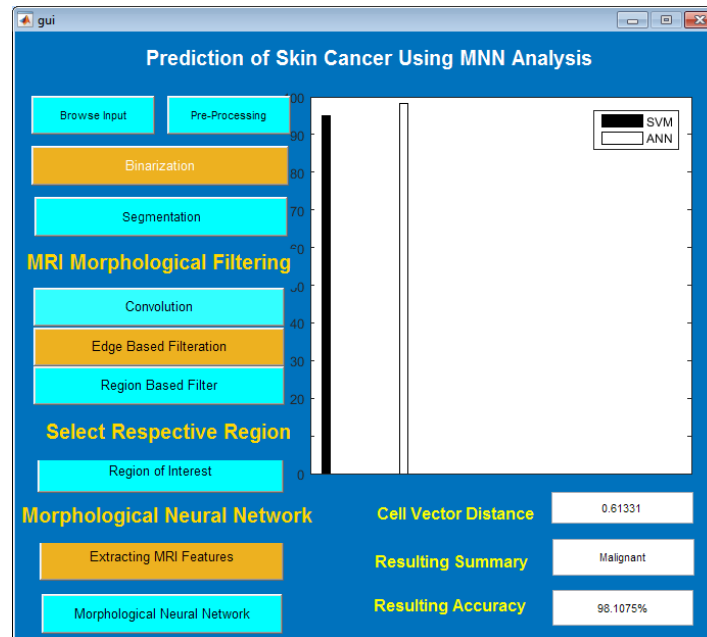


Fig.12 Feature Extraction

## VI. CONCLUSION AND FUTURE SCOPE

Developing precision medicine or a more effective personalized strategy for treating and managing Stage I patients requires a more accurate clinical marker and/or assessment tool to predict cancer prognosis (including cancer recurrence risk). Current studies mainly focus on identifying more effective genomic biomarkers, demographic factors, and other clinical variables. In this system, we investigated a new quantitative image feature analysis approach using skin images and demonstrated two new study results. It can be easily concluded that the proposed system of skin cancer detection can be implemented using gray level co-occurrence matrix and Multi-Support Vector Machine to classify easily whether image is cancerous or non-cancerous. Accuracy of proposed system is 95%. It is painless and timeless process than biopsy method. It is more advantageous to patients.

In future the proposed work is further enhanced by means of implementing a new classification strategy called Morphological neural Network (MNN) to improve the performance and accuracy level of the present system. For example in future work we can include MNN or any other powerful classification techniques to improve the accuracy to 98% and above, so that it would be helpful for medication field as well as patient end. In future the proposed work is further enhanced by means of implementing a new classification strategy called MNN to improve the performance and accuracy level of the present system. For example in future work we can include MNN or any other powerful classification techniques to improve the accuracy to 98% and above, so that it would be helpful for medication field as well as patient end.

## REFERENCES

- [1] J Abdul Jaleel, SibiSalim, Aswin.R.B, "Computer Aided Detection Of Skin Cancer", International Conference on Circuits, Power and Computing Technologies, 2013.
- [2] C.NageswaraRao, S.SreehariSastry and K.B.Mahalakshmi "Co-Occurrence Matrix and Its Statistical Features an Approach for Identification Of Phase Transitions of Mesogens", International Journal of Innovative Research in Engineering and Technology, Vol. 2, Issue 9, September 2013.
- [3] Santosh Achakanalli & G. Sadashivappa, "Statistical Analysis Of Skin Cancer Image –A Case Study", International Journal of Electronics and Communication Engineering (IJECE), Vol. 3, Issue 3, May 2014.
- [4] "Digital image processing" by jayaraman. Page 244,254-247,270-273.(gray level, median filter).

## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: [www.ijirset.com](http://www.ijirset.com)

Vol. 8, Issue 2, February 2019

- [5] Algorithm For Image Processing And Computer Vision. Page 142-145.(Thresholding)
- [6] Kawsar Ahmed, TasnubaJesmin, "Early Prevention and Detection of Skin Cancer Risk using Data Mining", International Journal of Computer Applications, Volume 62–No.4, January 2013.
- [7] M. Chaithanya Krishna, S. Ranganayakulu, "Skin Cancer Detection and Feature Extraction through Clustering Technique", International Journal of Innovative Research in Computer and Communication Engineering, Vol. 4, Issue 3, March 2016.
- [8] A.A.L.C. Amarathunga, "Expert System For Diagnosis Of Skin Diseases", International Journal Of Scientific & Technology Research, Volume 4, Issue 01, 2015.
- [9] Mariam A. Sheha, "Automatic Detection of Melanoma Skin Cancer", International Journal of Computer Applications, 2012.
- [10] Anshubharadwaj, "Support Vector Machine", Indian Agriculture Statistics Research Institute.
- [11] Maurya R, Surya K.S., "GLCM and Multi Class Support Vector Machine based Automated Skin Cancer Classification", "IEEE journal, vol 12, 2014.
- [12] HuW, Huang Y, Wei L, Zhang F, Li H (2015) Deep convolutional neural networks for Hyperspectral image classification. J Sensors 2015:258619
- [13] Ioannis G, Nynke M, Sander L, Michael B, Jonkman Marcel F, Nicolai P (2015) MED-NODE: a computer-assisted melanoma diagnosis system using non-dermoscopic images. Expert Syst Appl 42(19):6578–6585
- [14] Isasi AG, Zapirain GB, Zorrilla MA (2011) Melanomas non-invasive diagnosis application based on the ABCD rule and pattern recognition image processing algorithms. Comput Biol Med 41:742–755
- [15] Iyatomi H, Oka H, Celebi ME, Ogawa K, Argenziano G, Soyer HP, Koga H, Saida T, Ohara K, Tanaka M (2008) Computer-based classification of Dermoscopy images of melanocytic lesions on Acral volar skin. J Investig Dermatol 128:2049–2054
- [16] Krizhevsky A, Sutskever I, Hinton GE (2012) ImageNet Classification with Deep Convolutional Neural Networks. In: Proceedings of the Advances in Neural Information Processing Systems 25 (NIPS 2012) 1097–1105
- [17] Mohd A, Ram GK, Shafeeq A (2017) Skin cancer classification using K-means clustering. Int J Tech Res Appl 5(1):62–65
- [18] Na L, Xinbo Z, Yang Y, Xiaochun Z (2016) Objects classification by learning-based visual saliency model and convolutional neural network. Comput Intell Neurosci 2016:7942501
- [19] Qaisar A, Celebi ME, Carmen S, Fondón GI, Ma G (2013) Pattern classification of dermoscopy images: a perceptually uniform model. Pattern Recogn 46:86–97
- [20] Ramlakhan K, Shang Y (2011) A Mobile Automated Skin Lesion Classification System. In: Proceedings of 23rd IEEE International Conference on Tools with Artificial Intelligence, p 138–141
- [21] Sermanet P, Chintala S, LeCun Y (2012) Convolutional neural networks applied to house numbers digit classification. In: Proceedings of 21st International Conference on Pattern Recognition (ICPR '12), p 3288–3291
- [22] Sladojevic S, Arsenovic M, Anderla A, Culibrk D, Stefanovic D (2016) Deep neural networks based recognition of plant diseases by leaf image classification. Comput Intell Neurosci 2016:3289801
- [23] Somkid A, Jairaj P, Pawalai K (2011) Solving multiclass classification problems using combining complementary neural networks and error-correcting output codes. Int J Math Comput Simul 5(3):266–273
- [24] Vedaldi A, Lenc K (2016) MatConvNet: Convolutional Neural Networks for MATLAB. arXiv: 1412.4564v3 [cs.CV], 5 May 2016 ml
- [25] Wiharto, Kusnanto H, Herianto (2015) Performance analysis of multiclass support vector machine classification for diagnosis of coronary heart diseases. Int J Comput Sci Appl 5(5):27–37
- [26] Xiao-Feng L, Xue-Ying Z, Ji-kang D (2010) Speech Recognition Based on Support Vector Machine and Error Correcting Output Codes. In: proceedings of the 1st International Conference on Pervasive Computing, Signal Processing and Applications, p 336–339
- [27] Yan Z, Yang Y (2014) Application of ECOC SVMs in Remote Sensing Image Classification. In: proceedings of the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XL-2, ISPRS Technical Commission II Symposium, p 191–196
- [28] Yang Liu (2006) Using SVM and error-correcting codes for multiclass dialog act classification in meeting corpus. INTERSPEECH – ICSLP:1938–1941
- [29] Yushi C, Lin Z, Xing Z, Wang G, Yanfeng G (2014) Deep learning based classification of hyperspectral data. IEEE J Sel Top Appl Earth Observations Remote Sens 7(6):2094–2107
- [30] Zeiler MD, Fergus R (2014) Visualizing and understanding convolutional networks. ECCV 2014, Part I LNCS 8689:818–833
- [31] Zhigang Y, Yang Y (2014) Performance analysis and coding strategy of ECOC SVMs. Int J Grid Distrib Comput 7(1):67–76