Wider Necessity of Digital Image processing in Biomedical with its further scope

Pavankumar Naik, Arun Kumbi, Vishwanath Hiregoudar
Computer Science and Engineering Department,
Vishvesvaraya Technological University, Karnataka, India.

***Abstract*— In this paper a number of recent developments in medical imaging are outlined, with the focus being on the application of image processing techniques. Medical images are at the core of medical science and an enormous source of information that need to be utilized. Image processing techniques with regards to biomedical images are generally either used for the retrieval of images (Content Based Image Retrieval) or for analysis and modification of images. In this paper we give a importance, growth and feature of image processing techniques in Biomedical.**

***IndexTerms*—Biomedical Images and Information Technology, Biomedical Image Processing, Healthcare Informatics, Image Retrieval, Image Processing.**

I. Introduction

Information Technology (IT) has traversed all aspects of human life, and the past few decades have seen the influence of this technology in the field of healthcare and medicine. At the core of medical science are biomedical images – images of the human body that help in the understanding of the nature of human biological systems. These images may be at the molecular level or images of complete organs, organ systems, and body parts. These images are enormous sources of information and like any other source of information need to be tapped and analyzed to pave the way for better understanding. In understanding and gathering information from these images, the technique of image processing is of utmost importance. Image Processing is the process of modifying or interpreting existing pictures, such as photographs [9]. This paper studies the current state of technology and outlines the major areas in which image processing techniques are used with regards to medical science. It also looks at the current research work being done all around the world in the field.

II. Biomedical Images and Information Technology

Biomedical imaging concentrates on the capture of images for both diagnostic and therapeutic purposes. Snapshots of in vivo physiology and physiological processes can be garnered through advanced sensors and computer technology. Biomedical imaging technologies utilize either x-rays (CT scans), sound (ultrasound), magnetism (MRI), radioactive pharmaceuticals (nuclear medicine: SPECT, PET) or light (endoscopy, OCT) to assess the current condition of an organ or tissue and can monitor a patient over time over time for diagnostic and treatment evaluation.

The science and engineering behind the sensors, instrumentation and software used to obtain biomedical imaging has been evolving continuously since the x-ray was first invented in 1895. Modern x-rays using solid-state electronics require just milliseconds of exposure time, drastically reducing the x-ray dose originally needed for recording to film cassettes. The image quality has also improved, with enhanced resolution and contrast detail providing more reliable and accurate diagnoses.

The limitations of what x-rays could reveal were partially addressed through the introduction of contrast medium to help visualize organs and blood vessels. First introduced as early as 1906, contrast agents, too, have evolved over the years. Today, digital x-rays enable images to more easily be shared and compared.

Digital imaging gave rise to the CT scanner and allows physicians to watch real-time x-rays on a monitor—a technique known as x-ray fluoroscopy—to help guide invasive procedures such as angiograms and biopsies. No longer limited to simple anatomical imaging, current research is focusing on what can be gleaned through functional imaging. Biomedical engineers are using CT and MRI to measure the blood profusion of tissue; especially important after a heart attack or suspected heart attack. Researchers are also using functional MRI (fMRI) to measure different types of brain activity following strokes and traumatic head injuries. PET scans—which use a radioactive tracer to measure metabolic changes, blood flow and oxygen use—have also improved with technological advancements. PET scans enable researchers to compare, for example, brain activity during periods of depression based on the chemical activity in the brain.

Optical molecular imaging technologies represent a new area of research that can be used to image human cells and molecules without the need for a biopsy or cell culture. Using contrast or imaging agents that attach to specific molecules, disease processes, such as cancer, can be spotted before they render their effects at the level of gross pathology.

Optical coherence tomography (OCT) is a newer form of CT being used in research that constructs images from light that is transmitted and scattered through the body. The power of ultrasound is being used in conjunction with microbubbles. The microbubbles can be injected directly into a specific location and then burst via ultrasound to emit localized contrast agents for imaging, chemotherapy for cancer treatment, air to help dissolve clots, and genes or drugs which can more easily penetrate cell membranes that are weakened by ultrasound. New imaging techniques bring new means for peering into the human body, helping to reduce the need for more invasive diagnostic and treatment procedures.

From the discovery of X-ray by Roentgen in 1895, to the present day imaging tools like Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), the technology has progressed much. The advances in the imaging technology will continue as time progresses. However, today the focus of systems is shifting from medical imaging focus from the generation and acquisition of images to post processing and management of image data [10]. This is stimulated by the need to make efficient use of the data that already exists. Recent progress in imaging research has shown the potential the technology can have to improve and transform many aspects of clinical medicine. Figure 1 shows the linkage between the various research areas in Biomedical Imaging Systems. Within the area of biomedical image processing we see research currently being done on two major frontiers:

a) Image Retrieval

Image retrieval techniques refer to the tools employed to search for a particular image from a set of images which are usually stored in a database. The mechanism used is either text based or based on content of the image.

b) Image Processing.

Once the image has been retrieved, methods can be used to enhance, reconstruct, or allow automated analysis so as to highlight or point out areas that may be of interest to the user.

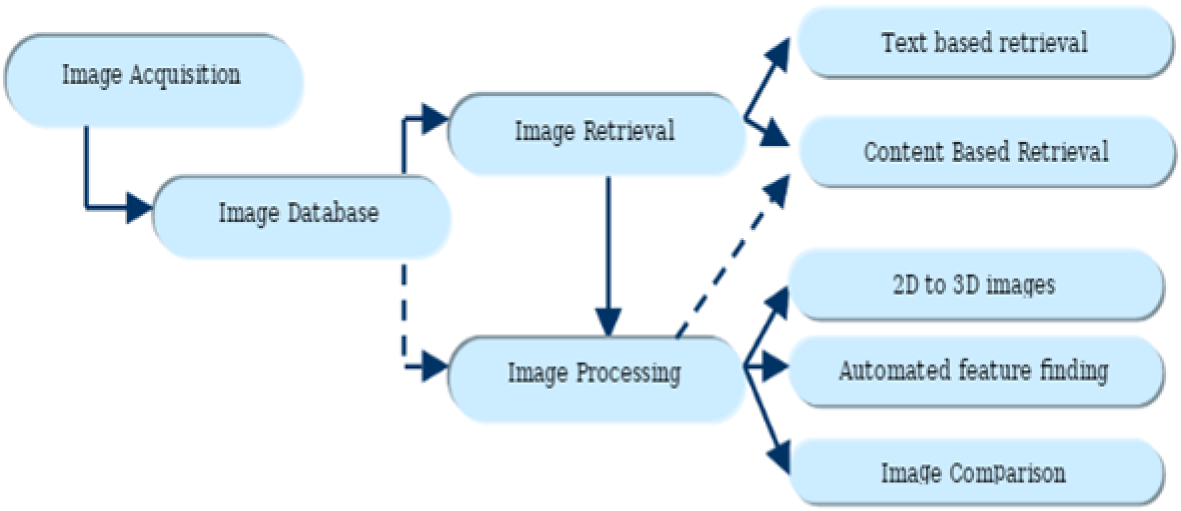

Figure 1. Main Research Area in Biomedical Imaging System.

Image Retrieval Research on biomedical imaging systems has it roots in early 1970s. The research was focused on developing systems that would enable image retrieval based on textual information about the image. Biomedical imaging systems developed over time to be text-based. A very popular framework of Image Retrieval was to first annotate the images by text, then use a text-based Database Management System to do the retrieval. Different representations of this were developed, and Picture Archiving and Communication Systems (PACS) found its place in many medical centers. However, as [11] pointed out, there exist two major difficulties in this approach, especially when the size of image collections is large (tens or hundreds of thousands of images). The first problem has to deal the vast labour required to manually annotate the images. The second difficulty is a result of the subjectivity in human perception – meaning different people may see things differently. This perceptual subjectivity may cause mismatches during retrieval. As large scale image collections emerged, the two difficulties faced by manual annotation became more and more acute. As a solution to this researchers started looking into image-based solutions. The most often referred to as content-based image retrieval (CBIR). Instead of manual annotation of images by text-based keywords, images would be indexed by their own visual content, such as color, shape and texture which can be extracted from the images themselves.

Another system QBIC, tells us how to retrieve images based on their visual image content combined with text and keyword predicates. Another system which retrieves images based on their perceptual content is SURFIMAGE. Many techniques in this research direction have been developed and many image retrieval systems have been built – both for research and for commercial usage. Systems have also been developed that allow users to submit shapes as queries. The first system developed to submit shapes as queries on the internet is Shape Queries Using Image Databases (SQUID),[20] developed at University of Surrey. Such techniques could be useful in the medical field as well. Systems allowing retrieval based on both semantic as well as visual properties have been developed, for example the VHD-MMS Agent Retriever. Use of statistical learning process, as well as Artificial intelligence agents has been studied to ensure easy retrieval of images.

In [12], Stanford University writes about a multi resolution based retrieval system called Simplicity that not only reduces the need for textual information but also, can handle, quickly and efficiently, the approximately one billion images that can be found on the internet. Much progress has been seen in the field of image retrieval – with various techniques studied and applied – generally in the context of the World Wide Web. These techniques can be modified and used to serve the medical community.

III. Biomedical Image Processing

Biomedical image processing is similar in concept to biomedical signal processing in multiple dimensions. It includes the analysis, enhancement and display of images captured via x-ray, ultrasound, MRI, nuclear medicine and optical imaging technologies.

Image reconstruction and modeling techniques allow instant processing of 2D signals to create 3D images. When the original CT scanner was invented in 1972, it literally took hours to acquire one slice of image data and more than 24 hours to reconstruct that data into a single image. Today, this acquisition and reconstruction occurs in less than a second. Rather than simply eyeball an x-ray on a light box, image processing software helps to automatically identify and analyze what might not be apparent to the human eye. Computerized algorithms can provide temporal and spatial analysis to detect patterns and characteristics indicative of tumors and other ailments. Depending on the imaging technique and what diagnosis is being considered, image processing and analysis can be used to determine the diameter, volume and vasculature of a tumor or organ; flow parameters of blood or other fluids and microscopic changes that have yet to raise any otherwise discernible flags.

The field of image processing has seen much research and advance since 1964, when the pictures of the moon transmitted by Ranger 7 were processed by a computer to correct various types of image distortions [13]. The application of the image processing techniques has seen its place in often unrelated problems, since they require the same underlying technology. In medicine, image processing techniques have been used for assisting in diagnosis and research. In the development of biomedical imaging systems, the idea of image retrieval goes hand in hand with the need for digital image processing. There are three primary application areas: firstly, image restoration, secondly, the processing of data for autonomous machines perception and finally the processing of images for improvement in human perception for example comparison or feature extraction.

Various techniques for image improvement like image enhancement and image restoration are used. Image analysis techniques including morphological image processing, edge detection, image feature extraction, image segmentation, shape analysis find much use in the medical field. More specifically, much research is being done to change the 2-dimensional images to provide a 3-Dimensional image structure, automated detection of certain specific features – which largely depends on what kind of images are being processed, and automated comparison of images to show the differences among them.

The three different methods used to segment biomedical images have been described in [14]. These three techniques are based on Entropy, Fuzzy Entropy and the Least Square Method. These methods are used to extract the components of an image.

In [15] Segmentation of anatomical structures, from modalities like computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound, is a key enabling technology for medical applications such as diagnostics, planning and guidance. More efficient implementations are necessary, as most segmentation methods are computationally expensive, and the amount of medical imaging data is growing. The increased programmability of graphic processing units (GPUs) in recent years have enabled their use in several areas. GPUs can solve large data parallel problems at a higher speed than the traditional CPU, while being more affordable and energy efficient than distributed systems. Furthermore, using a GPU enables concurrent visualization and interactive segmentation, where the user can help the algorithm to achieve a satisfactory result. This review investigates the use of GPUs to accelerate medical image segmentation methods. Morphological image processing is often used in combination with other segmentation algorithms such as holding, and is therefore included in this review. Examples of morphological techniques include filling holes, and finding the centerline of a segmented tubular structure.

[16] Provides a review of the current concepts in computer-aided diagnosis for CT colonography. The methods employed depend extensively on image processing. The challenges faced at current are the determination of useful features and improvement in classification strategies.

Many systems have been developed for the manipulation of biomedical images – both commercial as well as public domain software. Open software systems include I4 developed in [17] which explicitly supports the three spatial dimensions and the time dimension which is required for MRI and PET. disNei, as described in [18], is a graphical tool for image analysis and visualization allows a number of users to simultaneous and coordinately analyze medical images, create graphical models, navigate through them and superimpose raw data onto the models.

[19], has been involved in the design and implementation of computer-based techniques for comprehensive and fully interactive display and analysis of biomedical images since 1970s. The algorithms and programs that Mayo Clinic has developed have been integrated into a software system called Analyze, which allows detailed investigation of 3-D and 4-D biomedical images. The clinic also developed an extensible library of over 500 optimized image processing functions, called AVW for A Visualization Workshop. The centre has designed the "Virtual Reality Assisted Surgery Program (VRASP)" which takes image processing to another milestone in allowing surgeons to see 3D renderings of CT and MRO data and permit interactive virtual display manipulation.

IV. Literature Review

Digital image processing contains wide scope for researchers and scientists to work on various areas of science and engineering. Several algorithms have already been proposed and developed. This section makes a brief discussion on previous works and applications of image processing. Digital image processing is helpful for many applications and their analysis, which can be used in different applications like in vehicle detection from man image using aerial cameras [21]. One such application by using this concept can be applied in keyboard industry where poorly manufactured keyboards can be detected at manufacturing stage. In this type of applications an input image of the manufactured keyboard is fed to detect the missing key or damaged key. Similar concept has been used in Face Recognition [22-23], Facial Expression Recognition. Further with the advancement of

image enhancement techniques, a precise extraction of particular feature has become possible like number plate recognition from the detected vehicle and eyes, nose, ears, lip gesture from recognized face [24]. Digital Image Processing is applied in the fields of Computer vision, Face detection, Feature detection, Lane
departure warning system, Non-photorealistic rendering, Medical image processing, Microscope image processing Morphological image processing, Remote sensing, etc. Some of the applications of digital image processing are discussed as followings:

1) Computer Vision - Computer vision is a kind of automated watchdog, which uses both science and technology. Being a discipline from science, computer vision is related to theory for design of artificial systems that can acquire information from images. The image input may be of many formats, such as a video signal sequence, or multiple views from different cameras, or data input from a medical scanning machine. Examples of applications of computer vision include systems for controlling processes such as an industrial robot or an autonomous vehicle; for detecting events such as in visual surveillance or people counting; for organizing information such as for indexing databases of images and image sequences; for modeling objects or environments such as industrial inspection, medical image analysis or topographical modeling; for interaction such as the input to a device for interaction between a computing machine and human. [25-26].

2) Face Detection - In this method important facial features are detected and else are ignored. Face detection can be treated as a specific case of object class detection. The objective of face detection is to find the specified features such locations and sizes of a known number of faces. Various face detection algorithms are focused on the detection of frontal human faces. It is also an attempt to solve the more general and difficult problems of multi view face detection. [27-28].

3) Digital Video Processing - In different engineering and computing applications video processing is a particular and an important case of signal processing. Here the input and output signals are video files or video streams. Video processing techniques are used in television sets, VCRs, DVDs, video codec, video players and other devices. For example commonly only design of various systems and video processing methodology is different in TV sets by different companies.

4) Remote Sensing - Remote sensing is basically an acquisition of small or large scale information signals from an object or phenomenon, by the using various real-time sensing devices that are wireless in nature, or not in physical or direct contact with the object (such as aircraft, spacecraft, satellite or ship). Practically remote sensing is a collection of different data signals using variety of devices for gathering information on a given object or area. The monitoring of a parolee using an ultrasound identification system, Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), X-radiation (X-ray) and space probes are all examples of remote sensing. [29-30].

5) Biomedical Image Enhancement & Analysis - Biomedical image enhancement is very important issue for biomedical image diagnosis, the aim of this area is to enhance the biomedical images. In addition to originally digital methods, such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI), initially analog imaging modalities such as traditional applications like endoscopy or radiography are nowadays equipped with digital sensors. Digital images are composed by individual pixels to which points to discrete brightness or different color values. After biomedical image enhancement & proper analysis, they can be efficiently processed & objectively evaluated.

6) Biometric Verification - It refers to the automatic identification or recognition of humans by their behaviors or characteristics. Biometrics recognition is such an efficient type of identification and access control. It can also be used to recognize individuals in groups that are under observation. The purpose of such a technique is to ensure that the rendered services are accessed only by a legitimate user and no one else. A biometric system is theoretically a pattern recognition system that is based on acquiring biometric data from an individual. The operating principle is based on extracting set of defined features from the acquired data, and comparing this feature set against the template set in the database. Depending on the type and mode of application, a biometric system may work under verification mode or identification mode. [31-32].

7) Signature Recognition - Signature verification and recognition is also an important application, which is to decide, whether a signature belongs to a given signer based on the image of signature and a few sample images of the original signatures of the signer. Handwritten signatures are imprecise in nature as their corners are not always sharp, lines are not perfectly straight, and curves are not necessarily smooth. Furthermore, the fonts can be drawn in different sizes and orientation in contrast to handwriting which is often assumed to be written on a baseline in an upright position. Therefore, a robust handwritten signature recognition system has to account for all of these factors. [32-33].

8) Underwater Image Restoration & Enhancement - In Underwater Image processing, the basic physics of light propagation in the water medium comes into extinction. When the light enters into water, it exponentially attenuates with the depth of water level; therefore the visibility distance is affected and so limited. Underwater images suffer from different problems such as blurring, non uniform lightening, noise, low contrast, etc. Therefore, restoration & enhancement of underwater images is an essential area for research. Various filters are used in the enhancement methods to improve the image quality, to suppress the noise, to preserve the edges in an image and for smoothening of the image. [34-35].

9) Character Recognition - Character recognition, usually known as optical character recognition or abbreviated as OCR. It is mechanical or electronic translation of images of either handwritten or printed text (usually captured by a scanner) into machine editable text. It is a wide area for researchers in pattern recognition, artificial intelligence and machine vision. For many document input tasks, character recognition is the most cost effective and speedy method available. [36-37].

10) Medical Palmistry - Palmistry is a science which observes human palm by different aspects and derives conclusions about nature of the person. Since from ancient times, many civilizations like Indian, Chinese, Persian, Egyptian, Roman and Greek, people were used to get guidance about their present and future by means of palmistry. It includes attributes of human, like, health, psychology, intelligence, lifestyle and other related entities. Medical palmistry can be considered as one of the branches of palmistry. By using this medical palmistry, probable diseases can be identified by observing some symbols in human palms such as

iceland, cross, grill, spot, star, square and circle. Additionally shapes of palm and fingers also play very important role in such decision making for identification of deseases. [38].

.

V. FUTURE SCOPE

For almost all modalities, we are very close to the practical limits on spatial resolution. The speed of image acquisitions may increase, but sensitivity for detecting pathologies is limited by radiation dose or other safety considerations. From this, we may predict that, in contrast to the imperatives of the last 50 or so years, increases in image quality will not be major drivers of imaging technology in the near future. Instead, technical innovation will be used to reduce cost, scanning time and radiation exposures. We will no longer strive simply for the “best” images possible, but will make more prudent judgements about what compromises (in dose, speed, cost, resolution, sensitivity, patient tolerance) to make. If striving to improve imaging technology is destined to be less important, the role of the imaging physicist will need to be reassessed. One major goal should be to get a better understanding of what affects the signals used to construct images – the physical and physiological factors that modulate the behaviour of different energy forms in the body – to help interpret images better and derive more information. Remarkably, this has been a somewhat under-emphasized sub-discipline of imaging, but one that should drive the development of new techniques.

For each biological event associated with many pathological disorders, there is a physical signature that can be measured. This could be a change in tissue composition caused by fibrosis – which makes tissues stiffer – a physiological parameter such as reduced blood flow in arteries, or perhaps a change in an electromagnetic property such as conductivity or magnetic susceptibility. Physicists have excelled at devising ways to measure and map these properties, but a detailed relationship between the underlying events and imaging measurements is rarely available. Major gaps in our understanding of important contrast mechanisms in every modality and every application still remain.

The state of ignorance stops us from making the most of the data within images and impedes the development of more quantitative tissue characterization from images. So while functional MRI, for example, has revolutionized our ability to study the functional architecture of the brain, the precise relationship between the MRI signals used to map neural activity and the underlying neurochemical and electrophysiological processes are poorly understood. Similarly, although MRI differentiates tissues based on parameters such as spin relaxation times, we have no quantitative models of the causes of variations in relaxation that accurately predict the values actually measured. Bridging such knowledge gaps should be a major development area for imaging scientists in the future.

One result of a better understanding of the factors that affect image contrast should be the development of quantitative imaging biomarkers. This term has only recently entered the lexicon of imaging science but has a much longer history in, for example, the pharmaceutical industry. Formally, a biomarker is a characteristic that can be objectively measured and evaluated as an indicator of a specific biological process or a measure of a response to a stimulus, intervention or perturbation. A quantitative imaging biomarker is then a measurement of a characteristic that needs to be localized and/or mapped spatially.

Imaging reveals not only where processes occur, but can also report their spatial heterogeneity, and the relationships and variations between different regions. Clinical imaging today is still very qualitative – most images do not represent “absolute” properties (although CT is an exception). It is therefore hard to interpret measurements and to compare data taken at different times or using different pieces of kit. Quantitative imaging has grown a lot in recent years, allowing parametric maps of intrinsic tissue properties to be derived that reflect particular physiological phenomena or biophysical properties. But big practical obstacles to the adoption of quantitative imaging remain.

Another area where digital pathology is serving as a bridge between different length scales is in the recent interest to combine histomorphometry with molecular “omics” measurements for better disease characterization. Savage and Yuan (2016) recently presented FusionGP, a new tool for selecting informative features from heterogeneous data types and predicting treatment response and prognosis. Specifically they showed the ability of FusionGP in a cohort of 119 estrogen receptor (ER) negative and 345 ER positive breast cancers to predict two important clinical outcomes: death and chemoinsensitivity by combining gene expression, copy number alteration and digital pathology image data.

The digitization of tissue glass slides is clearly opening up exciting opportunities as well as challenges to the world of computational imaging scientists. It is clear that while computational imaging can clearly play a role in better quantitative characterization of disease and precision medicine, there still remain a number of substantial technical and computational challenges that need to be overcome before computer assisted image analysis of digital pathology can become part of the routine clinical diagnostic workflow.

On the technical side, one of the main challenges in the computational interpretation of digital slide images has to do with color variations in the tissue induced by differences in slide preparation, staining, and even whole slide scanners. Clearly decision support algorithms that aim to work on digital pathology images will have to contend with and be resilient to these variations. A second technical challenge has to with the fact that most whole slide digital scanners are only able to generate 2D planar images of the slides. Pathologists however routinely take advantage of depth information which is available on most microscopes. This dept or z-axis information is useful for a number of tasks such as in confirming the presence of mitotic figures. However some whole slide scanner manufacturers are already beginning to recognize the importance of accommodating the z-stack and we can anticipate 3d whole slide scanners soon. The availability of a new dimension to accompany the dense planar data will no doubt further put pressure on the algorithmic scientists to develop more intelligent and efficient approaches for detecting, segmenting, analyzing, and interrogating 3d stacks of digitized slide images. This issue of computational complexity will become further exacerbated with the spread and availability of multi-spectral imaging cameras for investigation of multiple different tissue analytes, where each tissue section could be imaged at multiple different wavelengths and hence comprise hundreds of accompanying images. Approaches like deep learning which attempt to perform unsupervised feature analysis and discovery will clearly need to be operating at much higher levels of computational efficiency and in conjunction with high performance computing and GPU clusters [1] to deal with the ongoing data deluge.

An area of substantial interest has been in the use of deep learning approaches for identifying and quantifying the number mitoses on cancer pathology images, a laborious and time consuming task for pathologists. In fact interest in this area has spawned a number of challenges for mitosis detection from routine H&E stained tissue images [2].

Despite the aforementioned challenges, the opportunities opened up by computational imaging of digital pathology are tantalizing. In spite of the reluctance thus far by the regulatory agencies to grant approval to whole slide scanned images for use for primary diagnosis, it is clear that the use of computer aided analysis with digital pathology will be part of clinical decision making in the near future. Apart from substantially aiding the pathologists in decision making, the use of computational imaging tools could enable the creation of digital imaging based companion diagnostic assays that could allow for improved disease risk characterization [3,4].

In [5] For the biomedical image computing, machine learning, and bioinformatics scientists, the aforementioned challenges will present new and exciting opportunities for developing new feature analysis and machine learning opportunities. Clearly though, the image computing community will need to work closely with the pathology community and potentially whole slide imaging and microscopy vendors to be able to develop new and innovative solutions to many of the critical image analysis challenges in digital pathology.

One very interesting image computing research area that digital pathology opens up is the ability to combine traditional handcrafted feature approaches with deep learning methodologies, thereby taking advantage of domain knowledge while also enabling the classifier to discover new features. Another exciting research avenue will be in the development of new data fusion algorithms for combining radiologic, histologic, and molecular measurements for improved disease characterization.

Computational imaging advances for digital pathology will finally begin to make pathology more quantitative, a field that has thus far significantly lagged behind radiology in this regard. By all indications, this transformation from qualitative to quantitative pathology is in the not too distant future[5].

[6] machine learning approaches appear to be taking over the field and are increasingly successful in image-based diagnosis, disease prognosis, and risk assessment. many scientific and practical challenges still need to be addressed to unlock their full potential, including how to train strong models on little data, how to improve access to data, how to best make use of the image structure and specific properties of medical imaging data in designing our models, how to interpret results, and how to apply these results in clinical practice.

In [7], how the line separating conventional algorithms and some learning-based ones are blurrier than people may think. perhaps these insights can help us design more accurate as well as more interpretable machine learning models, for the automatic analysis of medical images. computerized automatic dental radiography analysis systems for clinical use save time and manual costs and avoid problems caused by intra- and inter-observer variations e.g. due to fatigue, stress or different levels of experience.

In [8], benchmarks for a number of challenging tasks in dental X-ray image analysis, including algorithms for (i) anatomical landmark detection on lateral cephalometric radiographs, (ii) anatomical abnormality classification on lateral cephalometric radiographs, and (iii) dental structure segmentation on bitewing radiographs. The presented results will allow the objective comparison of existing and new developments in the field. All methods were evaluated using a common lateral cephalometric radiography dataset repository, a common bitewing radiography dataset repository, ground truth data, and unified measurements for assessment of the detection, classification and segmentation accuracy. Based on the presented results, we can conclude that recent methods achieved significantly improved performance on these challenging tasks. However, the presented results also demonstrate that accurately analyzing dental radiographs remains a challenging problem which is still far from being solved. It is expected that this benchmark will help algorithmic developments, and that more advanced approaches will be built and tested using the provided data repositories and benchmarks.

VI. CONCLUSION

Imaging will continue to advance and provide an essential set of tools for broad use in basic research, drug development, selecting treatments, assessing treatment response, assessing effects of drugs and more. Quantitative, robust and reliable imaging biomarkers will continue to contribute unique information for research and may be adopted for routine clinical applications. But in the near future, there is likely to be less emphasis placed on pushing the limits of image quality and more on understanding how to use images to their full capacity.

The future holds many prospects for the field of medicine from the applications that can be offered using the image processing technology. Much research is being carried out all around the globe and it takes only a couple of keyword searches to bring about a plethora of courses and research being done in the field. As time progresses, we need to consolidate our level of technological advancement so that it can be usefully implemented – this needs cooperation among people with different backgrounds – with a common aim of working for the benefit of mankind.

REFERENCES

[1] Jeong et al., 2010 (W.-K. Jeong, J. Schneider, S.G. Turney, B.E. Faulkner-Jones, D. Meyer, R. Westermann, R.C. Reid, J. Lichtman, H. Pfister Interactive histology of large-scale biomedical image stacks IEEE Trans. Vis. Comput. Graph., 16 (2010), pp. 1386–1395 http://dx.doi.org/10.1109/TVCG.2010.168).

[2] Veta et al., 2015 M. Veta, P.J. van Diest, S.M. Willems, H. Wang, A. Madabhushi, A. Cruz-Roa, F. Gonzalez, A.B.L. Larsen, J.S. Vestergaard, A.B. Dahl, D.C. Ciresan, J. Schmidhuber, A. Giusti, L.M. Gambardella, F.B. Tek, T. Walter, C.-W. Wang, S. Kondo, B.J. Matuszewski, F. Precioso, V. Snell, J. Kittler, T.E. de Campos, A.M. Khan, N.M. Rajpoot, E. Arkoumani, M.M. Lacle, M.A. Viergever, J.P.W. Pluim Assessment of algorithms for mitosis detection in breast cancer histopathology images Med. Image Anal., 20 (2015), pp. 237–248 http://dx.doi.org/10.1016/j.media.2014.11.010.

[3] Veta et al., 2012 M. Veta, R. Kornegoor, A. Huisman, A.H.J. Verschuur-Maes, M.A. Viergever, J.P.W. Pluim, P.J. van Diest. "Prognostic value of automatically extracted nuclear morphometric features in whole slide images of male breast cancer" Mod. Pathol. Off. J.U.S. Can. Acad. Pathol. Inc, 25 (2012), pp. 1559–1565http://dx.doi.org/10.1038/modpathol.2012.126.

[4] Lewis et al., 2014 J.S.J. Lewis, S. Ali, J. Luo, W.L. Thorstad, A. Madabhushi "A quantitative histomorphometric classifier (QuHbIC) identifies aggressive versus indolent p16-positive oropharyngeal squamous cell carcinoma" Am. J. Surg. Pathol., 38 (2014), pp. 128–137 http://dx.doi.org/10.1097/PAS.0000000000000086.

[5] Bychkov et al., 2016 D. Bychkov, R. Turkki, C. Haglund, N. Linder, J. Lundin Deep learning for tissue microarray image-based outcome prediction in patients with colorectal cancer M.N. Gurcan, A. Madabhushi (Eds.), Proceedings of the SPIE9791, Medical Imaging 2016, Digital Pathology, San Diego, California, United States (2016) http://dx.doi.org/10.1117/12.2217072 , 979115.

[6] medical image analysis volume 33, october 2016, pages 94–97 20th anniversary of the medical image analysis journal (media) machine learning approaches in medical image analysis: from detection to diagnosis http://dx.doi.org/10.1016/j.media.2016.06.032.

[7] Medical Image Analysis Volume 33, October 2016, Pages 91–93 20th anniversary of the Medical Image Analysis journal (MedIA) Machine learning for medical images analysis http://dx.doi.org/10.1016/j.media.2016.06.002.

[8] Medical Image Analysis Volume 31, July 2016, Pages 63–76 A benchmark for comparison of dental radiography analysis algorithms http://dx.doi.org/10.1016/j.media.2016.02.004.)

[9] Hearn, D., & Baker, M. P. (1997). Computer Graphics C Version (2nd Ed.). Prentice Hall Publications.

[10] Wong S. T. C., & Tjandra, D. A. (1999). A Digital Library for Biomedical Imaging on the Internet. IEEE Communications Magazine, 37(1), 84 -91.

[11] Rui, Y., Huang, T. S., & Chang, S.F. (1999). Image retrieval: current techniques, promising directions and open issues. Journal of Visual Communication and Image Representation, 10,

[12] Wang, J. Z. (2000). Region Based Retrieval of Biomedical Images. ACM Multimedia

[13]Gonzales, R. C. & Woods, R. E. (1993). Digital Image Processing. Reading, MA: Addison Wesley.

[14] Vitulano, S., Di Roberto, C., & Nappi, M. (1997). Different methods to segment biomedical images. Pattern Recognition Letters, 18(11-13), 1125-1131.

[15] Erik Smistad , Thomas L. Falch, Mohammadmehdi Bozorgi, Anne C. Elster[a], Frank Lindseth "Medical image segmentation on GPUs – A comprehensive review" http://dx.doi.org/10.1016/j.media.2014.10.012.

[16] Summers, R. M. (2002). Current concepts and future directions in computer-aided diagnosis for CT colonography. Third International Symposium on Virtual Colonoscopy, 68-72.

[17] Butterworth, E., (1998). I4- An Open 4-Dimensional BioMedical Imaging System. Retrieved from University of Washington, National Simulation Resource Web site: http:// nsr.bioeng.washington.edu/Software/I4/

[18] Alberola, C., Cardenes, R., Martin, M. Martin, M. A., Rodriquez-Florido, M. A., & Ruiz-Alzola, J. (2000). disNei: A collaborative Environment for Medical Images Analysis and Visualisation. Proceedings of Third International Conference On Medical Robotics, Imaging, and Computer Assisted Surgery, Pittsburgh, Pennsylvania, USA, 814-823.

[19] Robb, R. A., Hanson, D. P., & Camp. J. J. (1996). Computer-aided surgery planning and rehearsal at Mayo Clinic. IEEE Computer, 29(1).

[20] Mokhtarian, F. (2003). Search for similar shapes in the SQUID system: Shape Queries Using Image Databases. Retrieved from University of Surrey Web site: http:// www.ee.surrey.ac.uk/Research/VSSP/imagedb/demo.html

[21] A. K. Jain, "A handbook of Fundamentals of Digital Image Processing", Prentice Hall of India, 1989.

[22] R. C. Gonzalez & R. E. Woods, "Digital Image Processing", 3rd Edition, Prentice Hall of India, 2009.

[23] Madhuri A. Joshi, “Digital Image Processing - An Algorithmic Approach”, Prentice Hall of India, 2010.
[24] Aisha Ajmal & Ibrahim M. Hussain, “Vehicle Detection Using Morphological Image Processing Technique”, IEEE, 2010.
[25] Ye Zhang, Hongsong Qu & Yanjie Wang, "Adaptive Image Segmentation Based on Fast Thresholding & Image Merging", International Conference on Artificial Reality & Telexistence Workshops, pp. 308-311, 2006.
[26] Kwon Lee, Chulhee Lee & Seon Ae Kim, "Fast Object Detection Based on Color istograms and Local Binary Patterns", IEEE Region Conference TENCON 2012, Vol. 1, No. 4, pp. 19-22, 2012.
[27] Ritu Tiwari, Anupam Shukla, Chandra Prakash, Dhirender Sharma, Rishi Kumar & Sourabh Sharma, “Face Recognition usingMorphological Method”, IEEE, 2009.
[28] N. Patel & S. K. Dewangan, “An Overview of Face Recognition Schemes”, International Conference of Advance Research and Innovation (ICARI-2015), Institution of Engineers (India), Delhi State Centre, Engineers Bhawan, New Delhi, India, 2015.
[29]K. Geetha, Thanushkodi, Kishore Kumar, “New Particle Swarm Optimization for Feature Selection and Classification of Micro calcifications in Mammograms”, International Conference on Signal Processing Communications and Networking, pp. 458-463, 2008.
[30] Hadjiiski, Filev, P. Chan, J. Sahiner, B. Helvie, M.A. Roubidoux, “Computerized Detection and Classification of Malignant andBenign Microcalcifications on Full Field Digital Mammograms” Springer IWDM, Vol. 5116, pp. 336-342, 2008.
[31] Shailendra Kumar Dewangan, “Human Authentication Using Biometric Recognition”, International Journal of Computer Science & Engineering Technology (IJCSET), ISSN: 2229-3345, Vol. 6, No. 4, pp. 240-245, April 2015.
[32] S. Dewangan, P. Gupta, U. K. Sahu & I. Verma, “Realtime Recognition of Handwritten Words using Hidden Markov Model”, International Journal of Technological Synthesis and Analysis (IJTSA), ISSN: 2320-2386, Vol. 1, Issue 1, pp. 07-09, December 2012.
[33] S. Patil & S. Dewangan, “Neural Network based Offline Handwritten Signature Verification System using Hu’s Moment Invariant Analysis”, International Journal of Engineering and Advanced Technology (IJEAT), ISSN: 2249-8958, Vol. 1, Issue 1, pp. 73-79, October 2011.
[34] N. Patel & S. Dewangan, “Visual Quality Accomplishment of Underwater Images”, International Journal of Electrical and Electronics Engineers (IJEEE), ISSN: 2321-2055, Vol. 7, Issue 1, pp. 367-375, 2015.
[35] S. K. Dewangan, “Identification of Colors in Photographic Images Using Color Quantization”, Proceedings of International Conference of Advance Research and Innovation (ICARI, ISBN : 978-93-5156-328-0, pp. 318-322), Institution of Engineers (India), Delhi State Centre, Engineers Bhawan, New Delhi, India, February, 2014.
[36] Brijmohan Singh, Ankush Mittal and Debashis Ghosh, “An Evaluation of Different Feature Extractors and Classifiers for Offline Handwritten Devnagari Character Recognition”, Journal of Pattern Recognition Research, pp. 269-277, 2011.
[37] Soumen Bag and Gaurav Harit, “Topographic Feature Extraction For Bengali And Hindi Character Images”, International Journal of Signal & Image Processing, Vol. 2, No. 2, pp. 181-196, June 2011.
[38] Hardik Pandit & D. M. Shah, “Application of Digital Image Processing & Analysis in Healthcare Based on Medical Palmistry”, Proc. of International Conference on Intelligent Systems & Data Processing, pp. 56-59, 2011.