Chapter 1

Introduction

1.1 Introduction

Research on education has always placed more emphasis on verbal learning than on visual learning. With the proliferation of visual media for the dissemination of information, the capacity to understand, evaluate, and produce visual representations has become more important in the field of education. Visual illustrations help to capture attention and keep people motivated. Pictures and drawings play a crucial role in explaining scientific topics. They provide phenomena that are too small, large, rapid, or slow to be seen with the unaided eye. Visual representations also depict invisible or abstract events that are not directly observable or experienced [4]. The proverb “A picture is worth a thousand words” alludes to the belief that one still image can effectively communicate a complex idea. There are many real-world uses for digital images, such as in the domains of design, medicine, machine vision, remote sensing, pattern recognition, colour processing, and many more.

Medical science, a vital branch of natural science, focuses on understanding the human body, its structure and function in states of health, illness, and injury. It has led to models that help prevent disease, diagnose illness, and create therapies to reduce pain and restore health or function. The human body is highly complex, generating vast data on its properties. Researchers and clinicians face challenges managing this data to develop better diagnostics and treatments. Using images is an effective way to organize and interpret medical data, and their use will keep growing in both clinical medicine and biomedical research [5]. Medical imaging has advanced greatly since X-rays were discovered 120 years ago. Radiologists now use techniques like computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and ultrasound to see the body in detail [6]. As imaging technology becomes more common and data grows, analyzing medical images has become slower because it relies heavily on human effort. In the years ahead, artificial intelligence (AI) is set to revolutionize medicine. AI systems will be regularly used to detect diseases earlier, improve predictions, and develop more effective, personalized treatments while saving time and reducing costs [7, 8]. Computer assisted diagnosis using biomedical images is popularly employed for detection and diagnosis of diseases and have been crucial to the field of quantitative pathology. As a result, biomedical imaging technologies have advanced significantly in hospitals and medical diagnostic centres.

In order to effectively provide modern healthcare, medical imaging is becoming increasingly important. With the increasing popularity of use of medical images in modern healthcare, the image databases with a variety of image modalities have been developed. For the purposes of teaching, research, and evidence-based diagnosis, these image databases are indispensable. Medical images are vital in healthcare, supporting clinical decisions, medical research, and education by providing essential insights for diagnosis and treatment. Advancements in medical imaging technology, along with the rise in imaging equipment, have resulted in a continuous increase in the volume of medical images. Biomedical imaging has dramatically increased in hospitals and medical facilities for the purpose of patient diagnosis. Large image libraries are created because of the rapid growth of high-quality digital images. But unless this data is arranged to facilitate effective access, search, and retrieval, it cannot be utilised. Content-based biomedical image retrieval was created as a solution to this issue. Since 1970s, database management and computer vision, two significant research communities, have been pivotal in stimulating the intense activity in the area of image retrieval. These two aspects, one based on text and the other on visuals, examine image retrieval from various perspectives [9]. Previously, the process of searching through an image database relied on human annotation. This involved assigning keywords to each image in the database to indicate its semantic content, and then these keywords were used to index the images. Consequently, text-based image retrieval (TBIR) is the process of conducting a search for and obtaining pictures based on the keywords contained in the images. This TBIR approach has certain drawbacks, like when the volume of the picture collection expands larger, the manual annotation of each image becomes difficult. Furthermore, annotating an image according to human perception is subjective since several individuals may annotate images with the same visual components in different ways. Using an image as a query rather than words allows content-based image retrieval (CBIR) system to retrieve stored images from databases. CBIR is the procedure of locating similar images from large image repositories depending on their visual contents. The term content of the system refers to any colours, shapes, textures, or other information that can be learned from the image itself. The goal is essentially to rank "N" comparable images based on how relevant they are to the given query image. The semantic gap is a key factor that always reduces the performance of a CBIR system. A semantic gap is the discrepancy between high-level semantics and low-level characteristics, and a CBIR's effectiveness is dependent on how well it can mitigate this gap. Computer vision systems often extract low-level aspects (colour, texture, shape, spatial layout, etc.) out of images, whereas people are accustomed to high-level features (concepts) like text descriptors, keywords, etc. to describe images and gauge relative resemblance [10]. Smeulders et al in [11] describe the semantic gap as the " lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation". In order to overcome this difficulty, alternative approaches include looking for additional low-level features to enhance the functionality of the present CBIR schemes; also, if it is feasible, combining text-based retrieval with content-based retrieval is appropriate [12]. In image retrieval applications, the extraction of feature is always followed by another important part called feature matching, which is the measurement of distance in order to match the descriptors. The mostly used distance measure, which computes the dissimilarity between descriptors, is the Euclidean distance. Smaller the value of distance between two descriptors means, they are more likely to be alike; consequently, the corresponding images are treated as similar. Other standard distances are L1, Earth mover's distance, Cosine, Canberra, D1 and Chi-square. A pictorial representation of CBIR system is depicted in Fig 1.1.

On the other hand, image classification is one of the essential jobs in computer vision, supported by supervised learning techniques that classify unorganized input like images into predetermined number of categories or classes (i.e. labels) that are included in the time of training phase. The process of classifying aberrant medical images into distinct groups according to certain similarity features is known as medical image classification. Human perception serves as

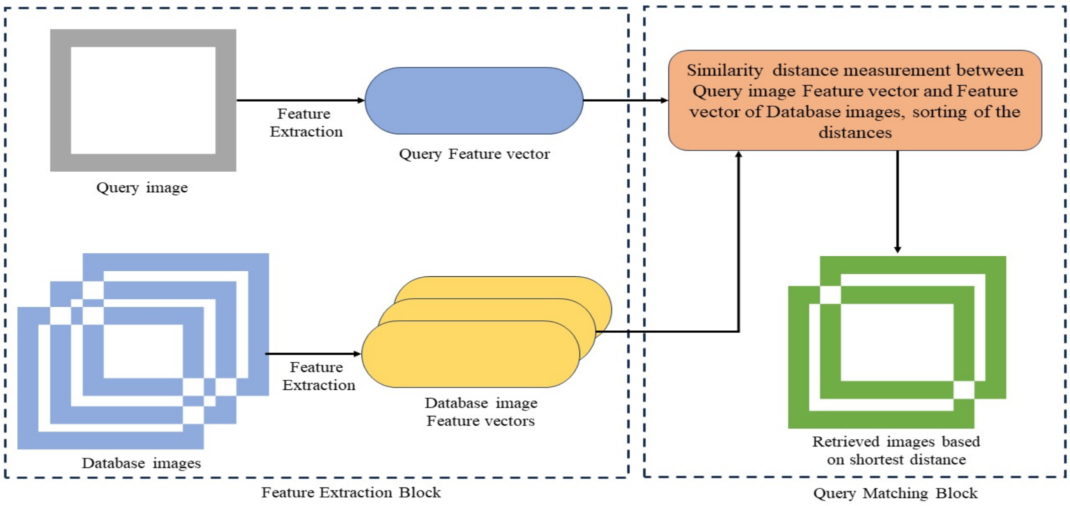

Figure. 1.1: Block diagram of the CBIR framework

the basis for traditional medical image classification techniques. But human vision is fallible. To get beyond the limitations of the traditional or manual image classification systems, several computer-aided diagnosis (CAD) techniques to support clinicians have been developed. These days, a variety of biomedical fields are practically using CAD frameworks that are created using various machine learning (ML) techniques [13]. Applications encompass a range of ailments and disorders such as the identification of brain tumours, skin cancer, lung cancer, alzheimer's disease, cataracts, diabetic retinopathy, glaucoma, breast cancer etc., among others. Naturally, the applications of ML go beyond diagnosis; they include big data research, personalized therapy, power system analysis, speech analysis and electric vehicle research etc. The roster is still growing. The medical field is one area where deep learning's latest surge in capability and acceptance is exemplified through image based implementations. The method of extracting progressively complicated information from images through multiple-stage process is the foundation of deep learning (DL). Highly improved results, for example in image retrieval and classification problems are the consequence of features that are captured at higher levels and gradually reflect more unique and unified aspects of the images [14].

Feature extraction, as utilized in image retrieval and classification, is the process of recognizing or fabricating discriminating features that characterise an image's content and help differentiate images from distinct classes.

The images have three main characteristics: colour, texture, and shape [15]. An essential component of human vision is color component. It is the visual characteristic that is most frequently utilized in image retrieval applications. Properties of an image, such as regularity, smoothness, and coarseness, are used to determine texture [16]. Texture characteristics are useful for retrieving and classifying images where specific patterns (textures) are linked to specific classes. They represent regular patterns in images. Images with distinct contour information are best suited for shape features. The most common way to obtain shape information is to identify the object of interest's edges. The texture-based features are more significant and considered as potent visual discriminators. To detect visual patterns, they are widely employed in image processing applications [17].

Texture feature can be segregated into global and local types depending on the interest regions that are used to compute texture details. A local feature descriptor calculates the visible characteristics of local sections to represent the picture content, while a global type views the entire image as one-entity and represents it with a limited number of attributes.

Researchers have preferred local descriptor over a global descriptor because of its many attributes, a few of them are:

- Robustness: The feature detection algorithm must identify the same feature regardless of changes in scale, rotation, translation, photometric distortions, compression artefacts, or noise.
- Repeatability: The algorithm for detecting feature must consistently recognize the identical features of an object or scene, a range of different viewing conditions.
- Accuracy: The algorithm for detecting feature must precisely locate image features, particularly for picture-matching tasks where accurate resemblance are essential for estimating epipolar geometry.
- Efficiency: The algorithm for detecting feature must rapidly identify features in new pictures to facilitate real-time implementations.

Due to the exceptional ability to catch very fine features in biomedical images, texture analysis has proven to be a valuable tool in resolving the computer vision and ML challenges. From a medical view, the texture based biomedical image retrieval is more usual since it is well- suited to recover the type of disorders or abnormalities available in the images.

The handcrafted or manually created features for retrieval and classification applications are developed by striking the balance between computer action and accuracy in order to capture particular features from images. Even after many years of use, the handcrafted features still remain an effective aid when used with many ML classifiers. DL schemes are gaining popularity due to their remarkable ability to classify and retrieve data. But it is known that in order to reach such remarkable results, they usually need a sizeable training data. DL approaches because of their automated feature extraction nature, can not employ heuristics to guide desired feature extraction for each unique task and experiences overfitting with insufficient training data. When there is a lack of data available, the hand designed features perform better than DL features. Biomedical sample continues to be a barrier to DL which is why learning of convolutional neural network (CNNs) is hampered. DL requires large data samples in order to generalize successfully on the learnt weights. Thus when it comes to biomedical classification tasks, transfer learning (TL) tasks are the most suitable choices. Hand designed features also has the benefit of having good correlation with the visible features that doctors choose, thus these attributes may be easily retrieved at object and spatial positions.

The handcrafted features had little inter-domain flexibility and demands a high degree of domain expertise. A few latest research [18, 19] have integrated handmade features with deep features using various schemes to provide a categorization of biomedical images, acknowledging the advantages derived from both.

In this dissertation, we focus on

1. Developing handcrafted texture feature descriptors for biomedical image retrieval applications.
2. Developing DL based and combined handcrafted and deep feature based frameworks for biomedical image classification applications.

1.2 Motivation

Because texture features in biomedical images can capture fine information from images, they are frequently employed in biomedical image texture descriptors. Thus makes them the most suitable for retrieving a disease category from image databases. Since the local pattern based feature descriptors can effectively describe texture feature, these descriptors have gained high popularity in biomedical image processing applications. Because of its efficiency and ease of computation, Ojala et al.'s local binary pattern [20] is a widely used local pattern based feature descriptor. Although in the discipline of medical image interpretation, the LBP and its different forms [17, 21–25] have shown promising results, it is noticed that they fail to extract very fine information present in the input images. This issue was solved by considering the transformation of local bit planes of images. Encoding each bit-plane (BP) independently is the main goal here because the highest to lowest BP slices of a given image extracts extremely coarse to highly fine image features. This strategy allows for the acquisition of maximum possible image information, particularly the fine information. In [26], the BP, the binary constituents of each neighbouring pixel in a given digital image are employed for calculating the local BP transformed values for every pixel utilizing an effective local BP transformation algorithm. Subsequently many improved BP based algorithms such as [27–30] were introduced in the field of biomedical image retrieval. All these techniques are based on circular sampling which is used to encode every individual BP of a given image. It has been noted that the current local BP based schemes can only capture isotropic micro-structure details from local circular scanning of each BP. A zigzag shaped sampling structure was developed in [31] for image classification application, with the aim of describing texture in the simple spatial environment. In zigzag sampling concept, with its numerous angle variation between the consecutive sample spots, has been demonstrated to be more effective than typical circular scan for collecting non uniform texture information [32]. Based on these observation we can anticipate that an effective non-circular sampling structure, (in spatial or BP environment) with more number of angle variations may further improve the capturing of non-uniform textures. The 2-D scanning patterns such as 2-D circular and 2-D zigzag sampling structures have some drawbacks too, for example they have limited ability of capturing multi-directional and inter-scale geometrical information. Three dimensional sampling patterns such as 3-D zigzag structures which are oriented at different directions, put in more angular changes in order to record more continuous changes in the local texture between the sample points. Not much work has been done in this field, despite the promising potential of such approaches to extract both regular and irregular textures. Further, it is observed that the features generated from an image at its current scale won't be able to give much distinct texture informations. In this connection, many studies have reported that the features when extracted from multiple scales show more discriminating information than the situation when features are extracted only from the current scale [33–36].

The coronavirus disease 2019 (COVID-19) pandemic due to SARS-COV-2 virus has significantly impacted nearly every aspect of human life. Given that COVID-19 was only recently identified, there is a dearth of information on the illness, its detection and its treatment. The World Health Organization (WHO) had classified this outburst as a pandemic in Jan, 2020. Accurate and quick methods for COVID-19 diagnosis are essential for enhancing the status of regular therapy and medical attention. The techniques like antigen testing, real-time reverse transcription-polymerase chain reaction (RT-PCR) are a few of the methods employed to identify COVID-19. The technique most commonly employed for this disease analysis is RT-PCR [37]. But this method takes a long duration to provide a result, frequently yields false negative findings and is not very sensitive to early detection [38]. Since the disease indication features of the lungs manifest before the symptoms emerge, the COVID-19 imaging components is crucial. Thus, radiological imaging through patients chest CT and X-rays might be very helpful in early diagnoses and treatment of COVID-19 [39]. As a sensitive technique for distinguishing COVID-19 from other lung conditions including pneumonia, the chest X-rays (CXRs) play a crucial part in the prompt identification and handling of this illness. It becomes strenuous to discriminate between COVID-19 and pneumonia patients since their symptoms are similar and overlap, affecting the human lungs. Due to the continually growing number of cases and the considerable risk of human mistake, the manual assessment of different radiological images is a slow process. Medical practitioners benefit greatly from the computer assisted analysis of medical images based on ML and DL which allows for the accurate and efficient examination of numerous ailment without a significant waste of time [40]. CNNs which have shown enormous growth over the last decade, are among the most popular models used for this task. The independent solutions typically concentrate on a particular aspect of the ML or DL framework building procedure, like models or architecture, the preprocessing schemes for input radiological images, addressing issues like class imbalance, data scarcity etc. that are frequently encountered with COVID-19 test datasets. Since COVID-19 is a fairly new kind of illness, there is a global shortage of imaging databases. In order to achieve better training, the DL algorithms however depend on a significant quantity of labelled data. Such medical datasets lack a large number of images which prevents DL models from learning efficiently and creating accurate models. The DL literature mostly addresses single network models for feature extraction where each network model may capture feature in a unique manner. It is believed that the collective blend of deep features from divergent models may make the feature more generous. Thus, the development of a dependable and precise DL model to diagnose COVID-19 from CXRs needs more investigation. In such data scarce situations, the extraction of comprehensive set of features is highly challenging and needs attention [41–43].

Diagnosing skin lesions (SLs) can be challenging even for expert doctors due to the presence of substantial inter-class visual similarities and intra-class variations among various skin cancer (SC) classes. To discriminate malignant classes from benign classes, the doctors must pay close attention to the tiniest of details, however the substantial similarity between classes and range of variations within each class further complicates the task. Furthermore, the presence of intricate skin disease may introduce extraneous elements that compromise the accuracy of color and texture descriptions in an image, thereby diminishing the categorization result. Further rigorous investigation is warranted to enhance the existing computer-aided ML and DL techniques with the intention of aiding in the highly accurate automatic identification of cutaneous lesions [44, 45].
DL has significantly transformed the automated diagnosis and management of diseases through its ability to accurately discern, define and categorize patterns within biomedical images. TL is extensively implemented in CNNs where the information is transferred from general object identification to domain-specific tasks within the context of the target job. It seeks to apply the data that was retrieved from one or more general tasks. TL has become an important component of a considerable quantity of applications, particularly within the domain of medical imaging in tandem with the development of DL.
There are several techniques that utilize the pre-trained DL CNN architectures as a foundational element in order to improve and construct an automated scheme for the diagnosis of SC. The existing pre-trained networks and their weights that they have learnt on huge datasets like ImageNet, can be utilized to develop improved DL models. While numerous effective DL models utilizing pre-trained CNNs for diagnosis of SC exist, not much attention is paid to the problems that consider the enhancement or modification of existing pre-trained CNN architectures in relation to SL classification. Also an in-depth investigation on how we might develop an ensemble of improved and modified pre-trained networks to further enhance their individual performance metrics in the task of categorizing dermoscopic images, requires careful consideration.

1.3 Thesis Contribution

An outline of the principal contributions of the thesis is given below:

(A) Two BP domain local pattern-based texture descriptors that employ arbitrary shaped sampling structures for retrieval of CT and MRI images, are proposed.

The inability of local pattern-based methods to capture extremely fine image features is one of the primary shortcomings. A couple of existing schemes first break down the input image into equivalent BPs which may capture extremely fine to extremely coarse image informations. A zigzag shaped sampling structure was recently developed in [31] for image classification application, with the aim of describing non-uniform textures in the raw spatial environment. Motivated from [31, 32, 35, 46], we introduce a multiscale local BP arbitrary shaped pattern (MS-LBASP) using BP based encoding, employing arbitrary shaped sampling structure with multiscale support, taking into account the issues of LBP based variants as well as the existing local BP based descriptors. It is shown that, in comparison to conventional circular sampling, the suggested arbitrary shaped sampling structures when combined with circular scans are very successful in characterizing both uniform and non-uniform textures.

The input image is first down-sampled into three different scales using the bicubic interpolation scheme. Next for each down sampled image, the corresponding BPs are extracted and both the uniform and non-uniform textures of each BP are captured through arbitrary and circular sampling structures. We introduced three effective arbitrary sampling strategies and implemented them in local BPs to integrate more random angle fluctuations to capture more irregular image textures together with very fine image details. For each multiscale image, the features are reduced by using mean based fusion and quantization. In contrast to current BP based methods, both sign and magnitude information are employed to compute the final connection between the fused local BP encoded values and the center pixel intensity. The analyses were conducted to judge the effectiveness of MS-LBASP. The experiments employed one MRI image dataset and two CT image datasets. The experiments signify that the MS-LBASP functions more effectively than the current relevant cutting-edge image descriptors.

Motivated from the success of the 2D arbitrary scanning structures and the concept of existing 3D zigzag sampling structures, we introduce another feature descriptor called local BP domain 3D oriented arbitrary and circular shaped scanning pattern (LB-3D-OACSP). In comparison to circular structures, zigzag sampling structures are able to preserve greater structural connections between surrounding parts. A few 3D zigzag scanning structures oriented in divergent directions in a 3D plane were introduced in [35, 36] to calculate the connectivity between a center and its neighbors. It was shown that this strategy outperformed conventional circular shaped sampling in terms of effective capturing of textural features. The multiscale 2D arbitrary shaped sampling structures i.e. MS-LBASP can capture more recurrent changes in local textures. The goal of this pattern is to introduce more angle variations between the sample locations. The MS-LBASP is demonstrated to be superior in terms of collecting more uniform and non-uniform textures along with the extraction of extremely fine to coarse image information due to the effective use of 2D arbitrary scanning structures and the capturing of features in BP domain. However, one of the shortcomings of the 2D arbitrary scanning structures in MS-LBASP is their extremely limited capacity to retrieve multidirectional information. Furthermore, interscale geometrical information, which offer more discriminative features that may be obtained with comparatively fewer dimensions, is not taken into account by MS-LBASP. Thus, inspired by [46–48] we introduced a few arbitrary and 3D circular scanning structures oriented at different directions in order to address these drawbacks of MS-LBASP and encode the inter scale geometrical details across the BPs corresponding to each multiscale image.

The LB-3D-OACSP in contrast to other scanning structures such as circular and zigzag, uses multi-orientational 3D arbitrary and 3D circular shaped scanning structures to calculate the connection between the reference and its surrounded neighbors in the BP domain in a 3D plane. With the intention of capturing more frequent change in the local texture, the multi-orientational 3D arbitrary shaped scans, in contrast to other scanning structures, give more continuous angular dissimilarity among the sample locations.

A 3D plane created using the corresponding BP of three, multi-scale images is applied with a total of 16 different discriminating 3D arbitrary, and 3D circular sampling structures oriented in different directions. This ensures the maximum extraction of inter-scale geometrical information across the scales, and effective capturing of both uniform and non-uniform textures. Three multiscale images are produced by applying Gaussian filter banks on the input image during the pre-processing phase. By encoding BPs, the LB-3D-OACSP descriptor is able to capture the majority of extremely fine to coarse image textures. Three widely used biomedical image datasets are utilized to assess the efficacy of LB-3D-OACSP with regard to average retrieval precision (ARP) and average retrieval recall (ARR). Comparing the experiments to numerous current relevant states of the art descriptors, they show an encouraging refinement in terms of %

ARP and %ARR.

(B) Two DL-based frameworks for classification of CXRs into COVID-19, Pneumonia and Normal classes are proposed.

In the first study, for the purpose of feature extraction from the input CXRs, we employ a variety of CNNs including ResNet-50, VGG-19, MobileNet-v2, Inception-v3 and DenseNet-201 based on TL. These CNNs are next incorporated with support vector machine (SVM) for the COVID-19 infection identification. To improve the contrast levels of the input X-rays, we utilize the advantage of CLAHE schemes. Since there is a shortage of images of individuals infected with COVID-19 virus, overfitting issues may occur, therefore, to get around this problem, in this study we utilize synthetic images produced by GANs. We show that the combination of fine-tuned Inception-v3 and VGG-19 features when introduced into the SVM classifier yields better outcomes than a great deal of previously documented methods for COVID-19 diagnosis. Our method is a promising scheme for COVID-19 diagnosis, since it was able to achieve an accuracy of 99.47%, sensitivity of 99.80%, specificity of 100%, precision of 100%, F1-score of 99.90% for dataset-1.

In DL frameworks, sometimes the automated feature learning and automatic feature extraction make it difficult to apply certain heuristics that doctors specify, to assist extraction of features for every unique activity. Also, the DL frameworks may experience issues like overfitting when the training samples are scarce. The main advantage of the hand engineered features is its strong correlation with the visual characteristics specified by physicians. In view of the benefits acquired from both deep and hand engineered features, an effective classification framework, to classify three classes i.e. COVID-19, pneumonia and normal from CXR images, is proposed. To calculate features from the original raw input spatial images, DL based scheme doesn't directly give much information on fine image details which is crucial for biomedical image analysis. The BPs of individual images possess information varying from fine to coarse levels. If effective hand-crafted pattern maps are created from these BPs, they may contain crucial discriminating details. Therefore, we can anticipate that the deep features computed from these hand engineered pattern maps may offer additional information to those computed from direct spatial input images. In order to predict 3 classes i.e. COVID-19, normal and pneumonia, we thus suggest combining deep features computed from raw spatial images with deep features calculated over suggested local BP based pattern maps. It is shown that the combination of these factors offers better discriminating power and works well in addition to the individual features. To create the final BP based pattern maps, we have integrated inter-scale features with multiscale information calculated from each BP. The suggested model outperforms the current techniques achieving an average accuracy of 100%,99.9%,98.8%,98.8% for datasets 1,2,3 and their combined form respectively.

(C) A multi class DL model for the diagnosis of skin-cancer from dermoscopic images is proposed.

Due to the dearth of labelled SL images, the SL categorisation problem using DL technique is a difficult undertaking. Therefore the implementation of data augmentation techniques utilizing GAN is imperative to aid in the categorization of SLs and empower doctors to arrive at more precise diagnostic judgement. We employed data augmentation based on cycle-GAN in order to enhance the task of SL categorization. An enhancement to existing pre-trained DarkNet-53, ResNet-50 and MobileNet-v2 architectures are proposed for robust feature extraction. A few new layers are inserted into DarkNet-53, ResNet-50 and MobileNet-v2 architectures enabling the extraction of more effective features. An improvement in all the classification judgement parameters have been obtained through the incorporation of these supplementary new layers into these three existing pre-trained architectures. An ensemble strategy is used to integrate all the individual outcomes of these modified architectures and their corresponding original forms in order to get a majority view, rather than depending on a single network. A majority voting technique is implemented to consider the choices that are received from each modified and its original DL model. The category that attains the largest number of choices is then chosen as the subject of the concurrent choice. A thorough assessment of various DL models is carried out utilizing ISIC2018 and ISIC2019 datasets that comprise seven and eight classes respectively. It was determined through experimentation that the proposed ensemble DL model exhibits better performance in comparison to the outcomes of individual CNN models.

1.4 Thesis Organization

The thesis is structured as follows:

- Chapter 1: ***Introduction***

  This chapter presents a background of investigations, motivation, thesis contributions and outline of this thesis.

- Chapter 2: ***Literature Review***

  This chapter presents a literature survey that encompasses several problems such as biomedical image retrieval, COVID-19 detection using CXR images and SL classification using dermoscopic images.

- Chapter 3: ***Texture descriptors based on arbitrary shaped patterns in bit-plane (BP) domain***

  This chapter starts with a very brief overview of relevant works on existing 2D and 3D sampling patterns in relation to local pattern based handcrafted feature descriptors. Chapter 3 presents two different feature descriptors in local BP domain that employ effective 2D and 3D arbitrary scanning patterns for retrieval of biomedical images. The experimental findings, which provide extensive validation of the superiority of the suggested procedures compared to other related schemes are also provided.

- Chapter 4: ***Deep learning-based techniques for classification of chest X-rays into COVID-19, Pneumonia and Normal Categories***

  This chapter presents two DL based frameworks for COVID-19 diagnosis from CXR scans. The experimental results, which validate the robustness of our suggested frameworks when compared to the most advanced methodologies, are also provided.

- Chapter 5: ***Deep learning-based classification of Skin lesions***

  This chapter introduces an effective DL based framework that utilizes CycleGAN based augmentation and ensemble of modified pre-trained CNN models for multiclass SL detection from dermoscopic images. The experimental results of the proposed work are demonstrated to be robust when compared to the most advanced approaches.

- Chapter 6: ***Conclusions and Future scope***

  The conclusion of the thesis is presented in chapter 6, which includes a summary as well as a discussion of prospective opportunities for further study.