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Robust Fuzzy and Sparse-Based Multispectral Digital Image Recognition Systems in Healthcare Applications

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Abstract: The development of systems for the recognition of digital images utilizing fuzzy logic and sparse representation (Robust Fuzzy and Sparse Multispectral Digital Image Recognition Systems, RF-SMDRS) can be very beneficial to healthcare. These systems combine fuzzy logic and sparse representation to achieve greater accuracy and reliability in the identification of digital images. The combination of fuzzy logic and sparse representation enables the management of the variations and complexities that naturally occur in digital imaging of the human body. Both fuzzy logic and sparse representation can improve the performance of RF-SMDRS across many types of healthcare applications. Fuzzy logic enables these systems to process images containing imprecise or fuzzy data. As such, fuzzy logic is most beneficial for processing digital medical images, where the shapes, textures, and intensities can vary greatly. By incorporating fuzzy logic into the design of RF-SMDRS, these systems can accurately and consistently identify and classify medical conditions, thereby assisting healthcare professionals in diagnosing and treating their patients. Sparse representation reduces the dimensionality of digital images, thereby speeding up RF-SMDRS image detection. By enabling faster and more accurate diagnosis of medical issues, RF-SMDRS may greatly improve patient outcomes in healthcare, which demands fast response times. RF-SMDRS's accurate, quick diagnosis of medical diseases could transform healthcare delivery. This research proposal will advance medical imaging and healthcare delivery.

Keywords: Fuzzy Logic; Sparse Multispectral; Patient Treatment; Cancer Detection; Image Recognition; Healthcare Application; Rapid Identification; Medical Conditions; Dimensionality Reduction.

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1. Introduction

Robust fuzzy and sparse-based multispectral digital image recognition systems are advanced computer vision-based automatic identification and classification systems for objects in digital images. Fuzzy logic is a mathematical concept used to model the lack of precision or uncertainty in data, allowing the representation of non-precise (fuzzy) information in digital images by assigning a degree of association to individual variables that define the information's degree of precision or uncertainty [1]. When fuzzy logic is used in an image recognition system, it enables the system to recognize the same object across varying forms and patterns and to overcome errors caused by noise in digital images. Sparse representations of a digital image represent the digital image data as a combination of a limited number of selected basis functions (descriptors) instead of representing the entire image as an array of pixels. The methodology presented here reduces the data requirements for image representation, thereby increasing resistance to external factors such as noise and computational constraints [2]. Additionally, when combined with fuzzy logic, sparse representation techniques can extract important image features for target recognition/classification using multispectral imagery. Multi-Spectral Imagery (MSI) refers to the collection of digital images across an area of the electromagnetic spectrum [3]. These digital photos can provide the user with much more detailed, specific, and richer information about the object(s) captured than traditional image recognition methods.

Before applying a classification method to the target object(s), the method must preprocess the image using fuzzy-logic methods to help eliminate or reduce inconsistencies and missing values within the image data. After this step, the method will extract critical image characteristics from the original image file using sparse-representation techniques. After extracting the critical characteristics from the original image file, they will be fed into a machine-learning classification methodology for the recognition/classification of target object(s) within the multispectral digital image data [4]. These systems can be used in a wide range of computer vision applications and support the use of fuzzy logic and sparse representations to achieve accurate image classification and recognition. Technical problems associated with this type of system exist that will impact performance and accuracy [5]. Some technical problems to be discussed in this section include noise interference in multispectral images [6]. There are many types of noise in multispectral images, including random variations, distortions, and other artifacts, which can lead to incorrect classifications. Noise interference is particularly problematic with sparse representations because of the compression effects from the sparse representation coding process; thus, these systems are more susceptible to noise interference than traditional image recognition systems. This significantly reduces the accuracy of these systems' ability to recognize correctly. A major issue with fuzzy logic systems is their lower robustness. Fuzzy Logic uses fuzzy sets and language-based rules to represent situations that lack precision or certainty.

Because fuzzy logic relies heavily on mapping input variables to their corresponding outputs, the results are highly sensitive to changes in the input variables. Due to their complexity and the labour-intensive nature of developing and fine-tuning rules for fuzzy logic systems, these methods may not achieve maximum accuracy. The same technical constraints exist for sparse representation methods. The assumption for sparse representation methods is typically that only a small number of non-zero coefficients carry most of the information for any one image. This assumption may be valid under certain circumstances, but not in real-world applications, and will lead to less-than-perfect image representations. Even sparse representation methods require many training images per image type to be properly trained; collecting these images may not always be feasible. In addition to these technical shortfalls, there will be limits on computational power and time constraints for processing and analyzing images collected by a hyperspectral sensor. It is due to these issues that any newly developed hyperspectral imaging technology will likely not be able to be utilised in real time. Therefore, the aforementioned issues pose numerous technical challenges that must be addressed to determine whether newly developed imaging technologies can be practically used. Fuzzy logic systems face challenges such as noise, limited robustness to data changes over time (in fuzzy models), limited support for sparse modelling, limited computational capacity, and time constraints. New algorithms and other measures to address these deficiencies will enhance the integrity and reliability of fuzzy logic systems [7].

1.1. Importance of Digital Image Recognition Systems in Healthcare Applications

Because advanced medical image detection and diagnosis systems provide highly accurate, timely information to healthcare professionals to develop more effective diagnostic and treatment plans, healthcare has widely adopted these systems. Medical Image Analysis is now among the most frequent uses of Digital Image Recognition Technology within the medical industry. The Digital Image Recognition Technology provides advanced image processing that enables the identification of many types of abnormalities within images that would otherwise be nearly impossible for humans to detect. Consequently, Digital Image Recognition Technology enables more precise and efficient Medical Image Analysis, allowing Doctors and Radiologists to perform faster, more accurate diagnoses. Also, as a result of Early Detection of Disease via Digital Image Recognition Systems, Patients receive appropriate treatment sooner and maintain better overall Health [8]. Digital Image Recognition Systems can help identify Tumors and other Lesions that would have been impossible for a Physician to identify without a Computerized Image Analysis System. By enabling earlier disease detection, digital image recognition systems enable faster, more effective treatment plans, resulting in improved Patient Outcomes. Additionally, information obtained from Digital Image Recognition Systems is important for developing Individualized Treatment Plans for Patient Care.

Doctors can make more informed decisions about a given patient's treatment thanks to the vast amount of information provided by the Digital Image Recognition System (DIRS). The Digital Image Recognition System's advanced capabilities also enable greater detail in the construction of treatment plans for patients, driven by the growing number of image-processing methods and levels of accuracy. The improved accuracy of Digital Image Recognition Systems leads to better patient outcomes and significantly reduced costs of healthcare services. In addition to being used for diagnosis and treatment, DIRSs are also very helpful to researchers in developing new medicines and medical technologies. Researchers can analyse large volumes of medical images to identify commonalities (or associations) among them, which, in turn, can lead to a better understanding of diseases and the development of treatments [9]. Based on their proven effectiveness at improving disease diagnosis, DIRSs also will help to identify prevention strategies; create individualized treatment plans; improve the quality of care, and therefore increase overall quality of life; provide more effective surgical procedures by improving surgeon precision; allow for faster diagnosis of algorithms and the ability to provide therapy sooner; and hopefully lower the medical costs associated with those patients once treated [10].

1.2. Methods for Digital Image Recognition Systems

The use of digital image recognition systems has increased significantly in recent years, driven by advances in AI and the processing of big data. Digital image recognition systems are technology-driven systems that use algorithms and machine learning to analyze and detect objects in digital images. Digital image recognition systems operate through feature extraction, pattern recognition, and classification [11]. In feature extraction, the digital image is divided into multiple segments, known as features, and each feature is then matched to a reference database containing digitally scanned images of various objects. When a user uploads an image into a digital image recognition system, the user will see the results as a text label(s) attached to the identified objects within the uploaded digital image [12]. Over the last several decades, researchers have developed many different types of digital image recognition systems that have proven effective for numerous tasks, such as face identification, vehicle automation, and patient diagnosis. However, digital image recognition systems have many limitations, including bias and limited accuracy, and require continued research and development.

1.2.1. Fuzzy-Based Digital Image Recognition Systems

The fuzzy-based Digital Image Recognition (DIR) System is an artificial intelligence system that analyses and classifies digital images using fuzzy logic and image processing technologies. These DIRs are typically used in applications such as object detection, image segmentation, and pattern recognition. A representation of the fuzzy-based DIR systems is given in companion Figure 1.

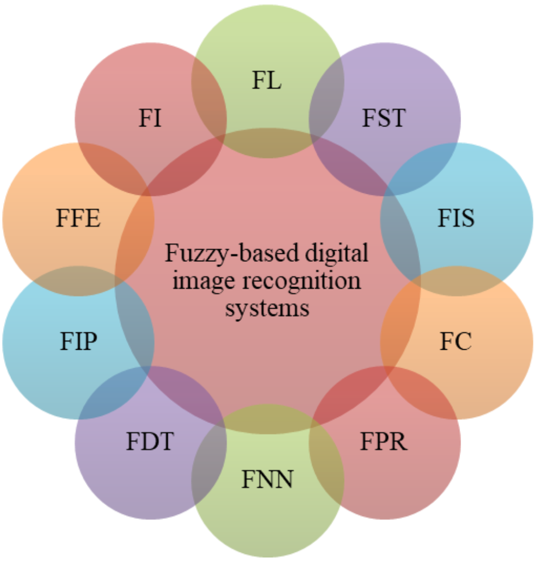

Figure 1: Fuzzy-based digital image recognition systems

Fuzzy logic is a type of mathematical logic that represents approximate rather than exact reasoning. It also differs from classical (binary) logic because it uses several different values between true and false (e.g., "somewhat true" or "mostly false").

Therefore, fuzzy logic is particularly useful when processing imprecise or uncertain data, such as in digital images. To implement fuzzy logic in image recognition systems, the first stage is often an image preprocessing step that enhances image quality and removes unwanted noise using various image processing techniques (e.g., smoothing, filtering, and media detection). After preprocessing, the original image is subdivided into smaller segments, called "pixels", which are assigned intensities and/or colours based on their pixel values. Once the image has been divided into pixels, the fuzzy logic method begins:

- **Fuzzy Logic (FL):** Fuzzy logic provides a mathematical method for producing the ability for a system to manage ambiguous or uncertain information effectively or imprecisely (when a number is not exactly known). Fuzzy logic enables the construction of a rule-based system that can accept incomplete or imperfectly defined values, generate accurate outputs, and produce consistent outputs across different operating conditions.
- **Fuzzy Set Theory (FST):** In fuzzy set theory, the way that you express a vague or ambiguous concept on an image is by specifying how much of each member belongs to the image at any given time. This is important because image data is highly uncertain, so defining the members of your image based on the percentage of similarity to others gives you a more complete picture.
- **Fuzzy Inference System (FIS):** A fuzzy inference system uses fuzzy logic to process data and then determine output values. Typically, a fuzzy inference system comprises rules, a database of linguistic variables, and a method for combining the outputs of each rule to produce a final crisp output.
- **Fuzzy Clustering (FC):** The primary purpose of fuzzy clustering is to group parts of an image that are similar to one another based on their degree of likeness. In turn, fuzzy clustering allows the segmentation of the image into components appropriate for more sophisticated investigation.
- **Fuzzy Pattern Recognition:** This technology analyzes an image's fuzzy attributes to categorize it. The classification phase relies on the degree of similarity among the image's attributes. Missing data and uncertainty do not affect the ability to classify the image, as it can be done based on the other information available. Fuzzy Neural Networks combine fuzzy logic with artificial neural networks to create intelligent image recognition engines. Fuzzy Neural Networks use fuzzy logic rules to process input data in the image recognition system and to create a neural network, thereby improving performance. Fuzzy Decision Trees use fuzzy logic to address uncertainty in image classification.
- **An example of this is when creating an Image Recognition Logic Map:** The Fuzzy Decision Tree generates many attributes to form a "weighted" set of rules that guide the image classification process. Fuzzy Image Processing uses fuzzy logic methods to improve image quality, minimize noise, enhance the detection of important features (edges, lines, etc.), and improve overall image quality; therefore, fuzzy methods are very important in the field of image recognition.
- **Fuzzy Examples:** Examples of fuzzy techniques used in image preprocessing include fuzzy feature extraction, where the features of an image are extracted using a fuzzily-defined method and provide an increased representation of the uncertainty and inaccuracy in the data; and fuzzy integration, where multiple image recognition processes are combined to create a process that improves both the ability and performance of image recognition.
- **Fuzzy Integration:** Users can manage multiple types of complex data and make reliable decisions by combining different fuzzy methods.

The degree of membership for each pixel is determined by applying multiple sets of rules and membership functions, based on the expertise of humans (e.g., facial recognition experts) and/or automated systems trained with machine learning algorithms (e.g., computer vision). For example, if an automated facial recognition software had been taught using numerous photos showing people's faces, those images, through the machine learning process, would form the knowledge base upon which it formed its decision of whether an image is or is not a human face, based on specific features typically found on human faces (such as two eyes, a nose, and a mouth). The membership functions would then assign a higher degree of membership to the pixels that most closely resemble these characteristics [13]. On the other hand, pixels that do not exhibit these characteristics will have a lower degree of membership. Once the system has assigned a degree of membership to all pixels, it combines this information to determine which objects or patterns are present in the image. Further processing may be required (such as clustering or classification), wherein pixels are grouped according to their degrees of membership and distinct objects or areas of pixels in the image are identified.

The fuzzy-based digital image recognition system will ultimately produce a classification or label for the image, indicating which objects or patterns it contains. Fuzzy Image Recognition Technology (FIRT) is useful for automatically categorizing photos, performing data analysis (e.g., feature extraction), or determining activities based on the information contained in an image. One advantage is that it enables imprecise or uncertain data to be processed correctly. In conventional image recognition systems, each pixel belongs to (or does not belong to) a given object, and this is determined by comparing the data against a predefined threshold (floor). Therefore, if the data is not adequately defined (uncertain), an incorrect classification can result when this approach is used to classify an image. Fuzzy logic provides a better approach to accurately and reliably classify images because it enables more cautious classification by establishing a continuum of classifications and accounting for uncertainty about what constitutes a particular classification. Thus, a FIRT utilizes fuzzy logic in addition to advanced Image Processing technology to produce accurate classifications of an image or set of images. FIRT's ability to process imprecise data makes it advantageous in many cases where traditional image recognition methods would not work effectively.

1.2.2. Sparse-Based Digital Image Recognition Systems

Digital image recognition systems that exploit sparsity (sparse-based digital image recognition systems) are examples of AI technology that enable machines to analyze and identify features in digital images. Sparse-based digital image recognition systems attempt to emulate how humans interpret and process visual information. Central to the operation of sparse-based digital image recognition systems is the concept of sparsity, which holds that the brain processes only pertinent information while discarding extraneous or irrelevant data. Therefore, by leveraging this property, humans can accurately and efficiently identify and recognise objects/information in images containing noisy or incomplete data. Sparse-based digital image recognition systems achieve similar results by applying sparse coding, which organises the entire reference image into a small number of representative feature vectors that capture all portions of the image in question. As a result, sparse representations provide an efficient means for digital image recognition systems to systematically process digital image data in a compressed format that is more compact than the original.

Consequently, digital image recognition will become a feasible and effective means for managing and performing image analytics within digital environments [14]. The sparse coding algorithms have several advantages; one of the most important ones is their ability to learn and process high-dimensional data so that they can recognize patterns in the image (complex patterns) as well as many other types of images. The other significant advantage is that they can handle large volumes of data, making them ideal for object and face recognition across large image collections. Dictionary learning is the method used to obtain sparse representations of digital images within a digital image recognition system. To create a dictionary of the most important features of an image from the input data, dictionary learning is performed iteratively. The dictionary created contains a set of sparse representations of the input data. These sparse representations are used to identify and classify new images. Figure 2 lists sparse-based digital image recognition systems:

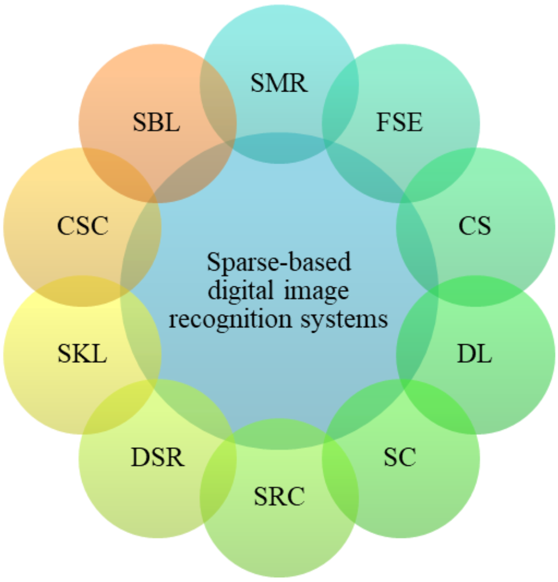

Figure 2: Sparse-based digital image recognition systems

- **Sparse Matrix Representation (SMR):** The representation of image data as a sparse matrix is referred to as SMR. Only non-zero pixels are stored in this representation. Hence, SMR has a smaller memory footprint than DN and requires less processing time, enabling real-time recognition.
- **Feature Selection and Extraction (FSE):** FSE is a technique used in sparse digital image recognition to reduce data dimensionality. Reducing the dimensionality reduces the complexity and computation expense of the recognition process.
- **Compressive Sensing (CS):** Another technology used by sparse-based Digital Image Recognition systems to collect and compress image data. Storage efficiency and transmission efficiency are thus enhanced, making it suitable for use in distributed recognition systems.

- **Dictionary Learning (DL):** In dictionary learning, a visual pattern dictionary is created by utilizing a set of images. Using a dictionary to sparsify image data improves recognition efficiency.
- **SC (Sparse Coding):** An approach that uses sparse methods to produce low-dimensional representations of high-dimensional data. The use of this technique enables efficient storage and processing of large volumes of digital images.
- **Sparse Representation Classification (SRC):** The purpose of Sparse Representation Classification is to produce a linear composite between an image and its basis, thereby allowing for quick and accurate identification of images by comparing their bases to one another.
- **Dictionary-Based Sparsity Representation (DSR):** DSR enables efficient image representation and recognition by using a dictionary of visual patterns, where each image is represented as a sparse linear combination of these patterns.
- **The Process of Sparse Kernel Learning:** In Sparse Kernel Learning, the objective is to learn a function that maps an input image to a higher-dimensional feature space. This allows efficient recognition of images with complex patterns.
- **CSC (Convolutional Sparse Coding):** A method that combines Sparse Coding and Convolutional Neural Networks to encode images as a set of visual features represented as a sparse linear combination. This therefore provides an efficient way to recognise images with complex visual patterns.
- **SBL (Sparse Bayesian Learning):** SBL is a statistical procedure used in Sparse Digital Image Recognition to estimate the likelihoods/probability distributions of images. Using this method, images can be recognised efficiently and accurately.

As previously mentioned, another major component of sparsity-based digital image recognition systems is neural networks. Networks that emulate neural connections (neurons) in our brains. Neural networks have been successfully used in recognition systems by providing the necessary training to recognize patterns and objects in digital images. In this application of digital image recognition, neural networks are trained on patterns in the sparse representations of images; the type of neural network commonly used in this area is a deep convolutional neural network (CNN). These networks process and analyze visual data in layers using filters; therefore, the more layers and filters in a CNN, the greater the probability that the network will successfully classify an image despite noise or obstructions from other objects. One key challenge in applying the concept of using a sparse data representation of an image in a digital recognition system is the need to acquire a larger volume of training data to achieve sufficient performance in image identification.

To achieve this performance level, the data used to train the digital image recognition system must adequately represent a wide range of variations (e.g., lighting, angles, and object types) while still providing a high degree of accuracy [15]. In response to this problem, researchers studied transfer learning, which enables the use of previously trained networks as a foundation for training on new tasks or datasets. By using transfer learning, sparsity-based systems can learn from smaller datasets, leveraging prior training that has provided the networks with general knowledge of visual patterns. Therefore, sparse-based systems for digital image recognition leverage advanced technologies that emulate the human brain's processing of visual information. The combination of sparse-coding algorithms and neural networks enables these systems to perform this function effectively and precisely, thereby providing a range of uses from autonomous vehicles to medical imaging to security systems.

1.3. Traditional Digital Image Recognition Systems

The process of acquiring an image involves capturing it via a physical medium, such as a camera or scanner. There are many different ways a digital image can be represented, including as an RGB, grayscale, or binary image. During the location and partition process, the next stage is to identify where the area of interest appears in the image you obtained. You can manually or automatically locate your area of interest, depending on your application. Identifying the location of the decimal point in images is particularly relevant for images containing numeric content, such as financial forms or documents. To determine the location of the decimal point, the image pixels need to be evaluated to identify patterns indicating its location. Identifying the decimal point location is therefore critical for obtaining accurate data during image extraction and subsequent analysis. In Figure 3, the construction of a traditional model has been illustrated. Binary format Binarisation is the process of producing binary (0s and 1s) pixel values for an image (grayscale or RGB), thereby eliminating most of the original image's detail and making subsequent image processing simpler. The slant correction technique is frequently applied to an image taken at an angle when it contains text or numbers, because image distortion can impair the ability to recognise characters or extract information from the image accurately. In slant correction, the angles at which lines and curves are oriented in the image are measured, and a mathematical transformation is applied to align them to their straight positions. Segmentation involves separating an image into smaller segments, each making it easier to extract certain features or patterns within the larger image. Segmentation methods can include thresholding, clustering, and edge detection, with differences in the methods depending on the characteristics of each image. Thinning images is another method for making all lines within an image of equal width. Thinning is important for handwriting recognition by making it easier to accurately identify characters when they are similar in shape.

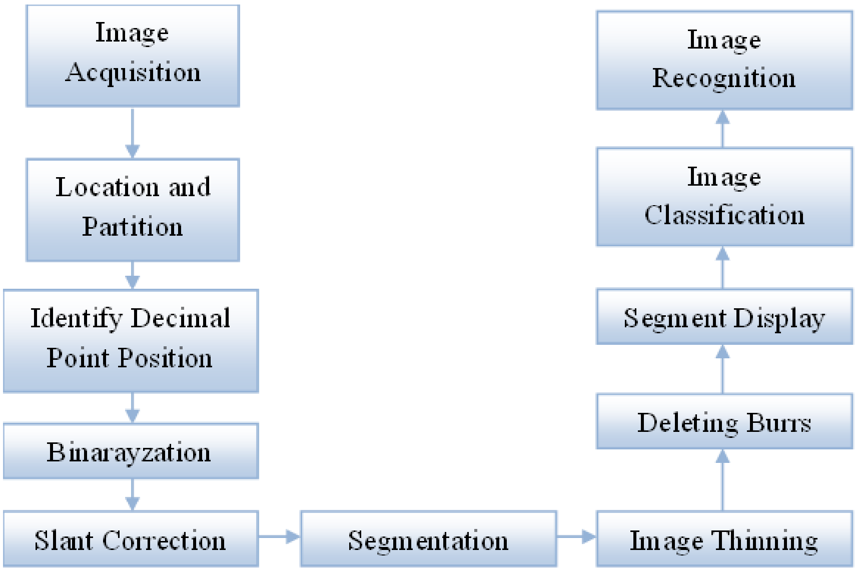

Figure 3: Construction of the traditional model

The ease of determining line thickness makes it easier to identify each letter and is helpful in many cases. Deleting burrs is the process of removing items that were not part of the original image before capturing it, such as things that were not present when the image was taken (such as noise, artefacts, and smoke from the capture). Removing burrs from the image will help keep it clearer and reduce distractions during future processing. The term "segment display" means displaying each segment, or section, of an image separately, which can be useful for digit recognition, as each digit is composed of different segments. When researchers separate and display each segment individually, they can identify the digit as a complete object. Image classification is the process of sorting and identifying images based on their content. This can be achieved through human judgment or algorithms and machine learning methods. Image classification plays an important role in the overall process of image recognition by automatically locating and classifying images based on their characteristics. Image recognition is the process of identifying and understanding the content of an image. Ultimately, it comes down to deep learning algorithms trained on large datasets recognizing objects, characters, or patterns in corresponding digital images.

1.4. Challenges in Digital Image Recognition Systems

- Finding ways to label training data has proven to be another major hurdle for fuzzy, sparse, weather-based multispectral digital image recognition systems. These systems require large numbers of accurately labeled training samples to work effectively due in part to the highly variable nature of real-world photographs, making it difficult to produce an adequate training set.
- Developing accurate and dependable recognition systems faces another hurdle: deriving meaning from pixels that are missing or contain gaps due to "holes" within a dataset of multispectral imagery. When these gaps cannot be reliably filled, reliability and, by extension, performance suffer.
- The third major hurdle in multispectral imagery recognition systems is determining or selecting the appropriate set of features that best characterise the sample image set. It is necessary to strike a balance between the degree of orthogonality among the selected features and their effectiveness; this balance will directly impact the accuracy and reliability of the recognition system developed.
- Class imbalance occurs when the sample sizes of the various classes within an image are unequal. The class imbalance typically leads the algorithm to itemise or classify more frequently into the larger class than the smaller class(es), thereby impacting its overall recognition rate.
- Additionally, the presence of so many spectral bands within a normal image creates a situation where the resultant data is at a higher dimension and therefore it is more difficult for an algorithm to extract useful features and/or patterns from the sample data; similarly, due to this high dimensionality, the classification and identification of the objects that comprise the sample data becomes considerably more challenging for the algorithm.
- Multispectral image recognition must deal with a myriad of sources of variability and noise within multispectral data; atmospheric variations are one such source, but not the only one. Electronic noise from the multispectral imaging sensor, along with environmental variables, leads to significant variability in recognition rates, making it less effective in certain situations. Consequently, recognition systems based on multispectral images, which require high accuracy, may be less effective due to the variability and noise in multispectral data.

- Another major challenge for multispectral image recognition systems is the trade-off between accuracy and speed in creating fuzzy and sparse-based systems. With the use of sophisticated algorithms and the development of fuzzy or sparse multispectral image recognition systems based on image processing, there are very real trade-offs between accuracy and speed in real-time applications. Achieving high-rate accuracy while maintaining high-speed processing in these systems is often difficult.
- One of the biggest challenges in developing multispectral image recognition systems is creating an effective means of generalizing them to new, readily inaccessible multispectral datasets. Generalizing to new, unknown multispectral data is particularly difficult when using fuzzy and sparse-based multispectral image recognition systems. As a result, a successful multispectral image-recognition system based on fuzzy and sparse methodologies must achieve the right balance between generalizability for the given application and accurate, reliable classification of multispectral images.
- Convergence is an issue with the iterative algorithms used during training of a fuzzy, sparse-based multispectral image recognition system, which may fail to converge to the desired optimal solution when working with complex or noisy data. If these problems occur, the recognition system may fail to achieve an optimal solution, thereby reducing its accuracy.
- The complex nature of a fuzzy, sparse-based multispectral image recognition system makes it less accessible to interpret its decision-making process when used to classify multispectral images. As such, fuzzy and sparse-based multispectral image recognition systems will lack transparency, as it is challenging to identify and address potential sources of bias or error.

2. Related Works

Multispectral digital imaging systems in healthcare are high-tech systems that use multiple spectral bands (wavelengths) of light/energy to capture and identify images of the human body, composed of different types of tissues and structures. These systems operate by illuminating the tissue or structure of interest with several different bands of light to reflect the data collected from that illumination. The collected data is then processed using specialised software algorithms to assist in identifying and analysing the reflected images. This enables the medical field to locate and analyze tissues or abnormalities that cannot be visually detected with the naked eye. They have a wide range of uses across multiple disciplines, including radiology, dermatology, and surgical procedures, enabling much higher diagnostic accuracy and more efficient treatment planning. Table 1 contains the complete analysis, along with a comprehensive list of Tables related to Table 2, and their corresponding SWOT analyses for fuzzy-based multispectral digital imaging recognition systems.

Table 1: Comprehensive analysis of fuzzy-based multispectral digital image recognition systems

Authors	FL	FST	FIS	FC	FPR	FNN	FDT	FIP	FFE	FI
Gavade and Rajpurohit [16]	✓									
Vakilian and Saradjian [17]	✓									
Zhang et al. [18]		✓								
Yang et al. [19]		✓								
Wan et al. [20]			✓							
Zare et al. [21]				✓						
Guo et al. [22]					✓					
Yu et al. [23]					✓					
Gao et al. [24]						✓				
Kumar and Suresh [25]							✓			
Madhu et al. [26]								✓		
Mullah et al. [27]								✓		
Wang et al. [28]								✓		
Ozigis et al. [29]									✓	
Liu et al. [30]										✓

FL - Fuzzy Logic; FST - Fuzzy Set Theory; FIS - Fuzzy Inference System; FC - Fuzzy Clustering; FPR - Fuzzy Pattern Recognition; FNN - Fuzzy Neural Networks; FDT - Fuzzy Decision Trees; FIP - Fuzzy Image Processing; FFE - Fuzzy Feature Extraction; FI - Fuzzy Integration.

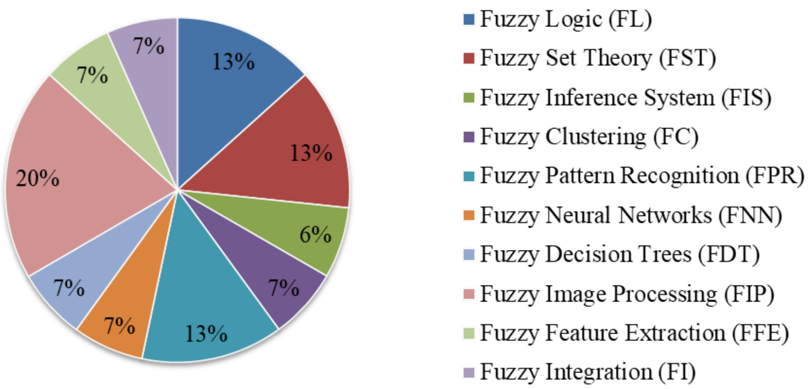

Figure 4: The models discussed in fuzzy-based systems

Figure 4 shows the models discussed in fuzzy-based systems (Table 2).

Table 2: SWOT analysis of fuzzy-based multispectral digital image recognition systems

Authors	Advantage	Limitation
Gavade and Rajpurohit [16]	Improved my accuracy in land area classification through the combination of sparse-FCM and deep learning techniques.	Limited availability of multi-spectral satellite images for training the deep learning model.
Vakilian and Saradjian [17]	Flexibility in handling a wide range of prior knowledge for image fusion due to its object-based approach.	It does not apply to multidimensional data fusion.
Zhang et al. [18]	Improved spectral resolution for enhanced analysis and interpretation of remote sensing data.	Possible limitation: Requires high computational power.
Yang et al. [19]	Improved image quality with high-resolution details by combining low-rank and fuzzy fusion techniques.	Loss of image quality due to potential distortions caused by the fusion and detail supplement process.
Wan et al. [20]	Efficient and accurate identification and extraction of spectral signatures from hyperspectral imagery, improving spectral unmixing performance.	Limited applicability to remote sensing images with complex and highly variable spectral signatures.
Zare et al. [21]	Improved spatial and spectral resolution for better object identification and classification in remote sensing applications.	Limited to images with specific spectral bands, making it less applicable to images with varying spectral bands.
Guo et al. [22]	Efficient identification and classification of targets, resulting in accurate and reliable information extraction for various applications.	Limited applicability due to the use of only fuzzy clustering, neglecting other classification algorithms.
Yu et al. [23]	Improved accuracy in assessing winter wheat growth using multiple spectral data from UAVs.	Reliability may be affected by limitations in the accuracy and consistency of data collected from UAVs.
Gao et al. [24]	Improves dimensionality reduction by using a combination of sparsity, deviation, and robustness techniques.	Limited by high sensitivity to outliers, resulting in potential inaccuracies and loss of robustness in data analysis.
Kumar and Suresh [25]	Improved accuracy in satellite image classification through the use of fuzzy logic and neural networks.	Complex and difficult to interpret due to the use of multiple methods, making it challenging to identify the source of errors.
Madhu et al. [26]	Improved accuracy by capturing and utilizing subtle variations in the local spatial characteristics of remote sensing images.	Limited application in complex environments with high variability and mixed land cover.
Mullah et al. [27]	Improved resolution/spatial enhancement is valuable for medical imaging, land use, remote sensing, and environmental monitoring.	There is a need for greater accuracy due to reliance on sparse representations and the inability to fully capture complex spectral features.

Wang et al. [28]	Efficient extraction of high-dimensional features with improved generalization capabilities for image recognition tasks.	Requires large amounts of data for effective discriminative block representation learning.
Ozigis et al. [29]	Improved accuracy in detecting oil pollution through the integration of multiple remote sensing technologies and sophisticated analysis methods.	There is a need for more accuracy in remote sensing techniques due to factors such as cloud cover or sensor limitations.
Liu et al. [30]	More accurate and detailed representation of multispectral imagery, resulting in improved classification and identification capabilities.	Limited to multispectral imagery, it may not work well with other types.

Table 3 presents the comprehensive analysis, and Table 4 presents the SWOT analysis of fuzzy-based multispectral digital image recognition systems.

Table 3: Comprehensive analysis of sparse-based multispectral digital image recognition systems

Authors	SMR	FSE	CS	DL	SC	SRC	DSR	SKL	CSC	SBL
Zhang et al. [31]	✓									
Cardone et al. [32]	✓									
Kusnik and Smolka [33]	✓									
Deka et al. [34]		✓								
Meenakshi et al. [35]		✓								
Leena et al. [36]			✓							
Sun et al. [37]				✓						
Kumar et al. [38]					✓					
Alshehri [39]						✓				
Wang et al. [40]						✓				
Yu et al. [41]							✓			
Zhang et al. [42]							✓			
Choudhuri and Halder [43]								✓		
Cao et al. [44]									✓	
Uma Maheswari and Rajesh [45]										✓

SMR - Sparse matrix representation; FSE - Feature selection and extraction; CS - Compressive sensing; DL - Dictionary learning; SC - Sparse coding; SRC - Sparse representation classification; DSR - Dictionary-based sparse representation; SKL - Sparse kernel learning; CSC - Convolutional sparse coding; SBL - Sparse Bayesian learning.

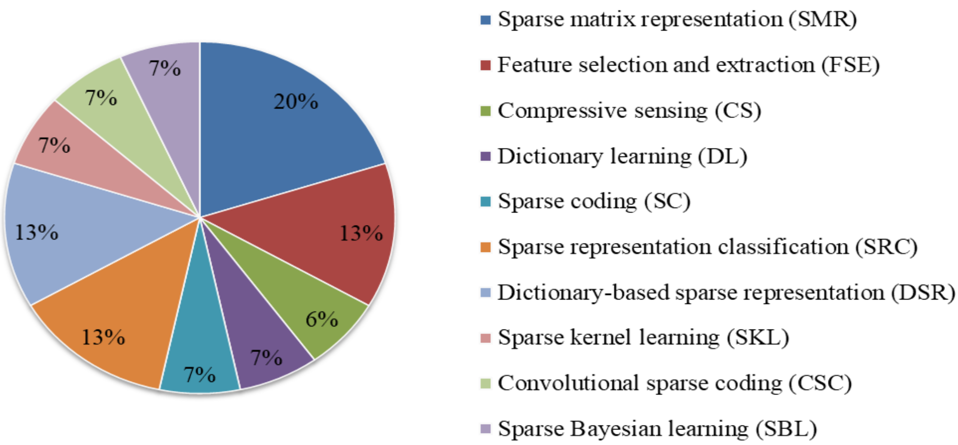

Figure 5: The models discussed in sparse-based systems

Figure 5 shows the models discussed in the context of sparse-based systems (Table 4).

Table 4: Comprehensive analysis of fuzzy-based multispectral digital image recognition systems

Authors	Advantage	Limitation
Zhang et al. [31]	Efficient and accurate identification and sorting of multicoloured fabrics, saving time and labour costs	Difficulty recognizing subtle colour variations due to limitations in sensor sensitivity or image noise interference.
Cardone et al. [32]	Improved accuracy in identifying objects within remote sensing images through the use of fuzzy logic and thresholding techniques.	Reliance on manual input for determining fuzzy membership values can make the method time-consuming and subjective.
Kusnik and Smolka [33]	Improved battery life for IoT devices by reducing energy consumption through efficient cache localization.	Inapplicable for situations where devices frequently move and communicate with different peers, causing frequent cache updates.
Deka et al. [34]	An effective noise-reduction method that preserves image quality and minimizes loss of important details.	The filter is not suitable for images with extreme levels of mixed Gaussian and impulsive noise.
Meenakshi et al. [35]	One advantage is that it can effectively enhance image resolution while preserving important remote-sensing features.	Limited to remote sensing images, it may perform poorly on other types of images.
Leena et al. [36]	Efficient and accurate identification of fabric images for quick and targeted retrieval.	Limited to fabric images, it may not apply to other types of images.
Sun et al. [37]	One advantage is the ability to accurately extract and classify roads by considering contextual information and geometric relationships between objects.	Limited by resolution and a small spectral band range, which can lead to misclassification and inaccurate road delineation.
Kumar et al. [38]	The improved spectral range of the imaging system captures more detailed information in multispectral images.	One limitation of the proposed nine-band multispectral imaging system is its limited ability to capture and reproduce fine spectral details.
Alshehri [39]	Improved accuracy in classifying histopathological images using fuzzy SVM and within-class relative density.	Possible overfitting due to the small dataset used for training the feature extractor.
Wang et al. [40]	Improved accuracy of image search results due to advanced neural network prediction capabilities.	Subjective results due to variations in image interpretation and limited generalizability to different types of images.
Yu et al. [41]	A major advantage of FusionNet is that it can successfully fuse hyperspectral and multispectral images without the need for labelled training data.	FusionNet requires substantial training data to achieve optimal results.
Zhang et al. [42]	The sparse mix-attention mechanism enables more efficient and accurate fusion of multispectral and hyperspectral images.	It does not apply to other domains beyond multispectral and hyperspectral image fusion.
Choudhuri and Halder [43]	More accurate and efficient nuclei segmentation compared to traditional methods.	Low accuracy in identifying nuclear boundaries.
Cao et al. [44]	It leverages the strengths of both ensemble modelling and genetic algorithms to improve land cover classification.	Assumes homogeneous training data and may struggle with datasets that have a class imbalance or multiple classes with similar spectral signatures.
Uma Maheswari and Rajesh [45]	High accuracy of classification results due to the integration of advanced QIM-DCT, PSO, and SVM methods.	The complexity of implementation for large datasets.

3. Analytical Discussion

Multispectral imaging systems are very important in healthcare, as they enhance doctors' ability to analyse medical images by revealing many more details than traditional black-and-white images. With a multispectral imaging system, you can create images at multiple wavelengths of light, enabling the identification of different tissues and organs, as well as abnormalities that may not be visible in a black-and-white image. A multispectral imaging system accomplishes this by utilising spectral analysis. The information obtained from a multispectral imaging system is then transmitted to the healthcare professional through numerical quantification of the images, thereby providing a more accurate and detailed basis for diagnosis and treatment decisions. The overall benefit of multispectral imaging systems to healthcare is improved image quality and efficiency in diagnosing, treating, and caring for patients.

3.1. Purpose of the Study

The use of robust fuzzy systems with sparse-based multispectral digital image analysis is a sophisticated image analysis technology in health care that enables precise identification/classification and, therefore, improved diagnostic, treatment planning, and medical research by combining fuzzy logic with the sparse representation of the digital dataset. Robust fuzzy/sparse-based image recognition systems effectively address many problems associated with highly variable, noisy, and fuzzy images by leveraging fuzzy logic and sparse data representations. Fuzzy Logic enables the inclusion of uncertain (fuzzy) information in decision-making. This is especially true in the medical imaging field, where irregularities and variations within medical images themselves can create challenges for conventional binary logic systems. Using a fuzzy approach enables the development of an in-depth, more adaptable method for identifying medical images, leading to greater accuracy and the trustworthiness of the generated data. On the other hand, sparse representation focuses primarily on the most important or relevant features of the data, rather than examining all available features.

In healthcare imaging, for example, it means identifying and extracting the most important visual characteristics or attributes from the image (taking into account the patient's condition and treatment history), while ignoring all non-essential or duplicated information. Sparse representation allows fewer elements to be processed during recognition. It also enhances both the speed and effectiveness of the IT and computing processes used for image analysis and recognition. Integrating fuzzy logic with multispectral imaging (multiple spectral bands) for sparse data representation can enhance the healthcare system's ability to process and analyse large datasets generated from healthcare images. By leveraging fuzzy logic to derive meaning from ambiguous and indeterminate data, while also implementing sparse data representation to isolate the most relevant and significant features of each piece of data collected, this type of system enables an organization to increase the frequency of accurate and consistent image recognition results, thus allowing for improved patient outcomes and patient care-oriented decision-making. Ultimately, the objective of a robust, fuzzy, and sparse multispectral digital image recognition system for healthcare is to enhance the overall effectiveness, efficiency, and quality of the healthcare system, thereby maximizing the patient experience and advancing medical research.

3.2. Impacts of the Study

In recent times, there has been an increase in the use of digital imaging technology within healthcare sectors due to the improved capabilities of newer-generation automated systems to analyse digital images. Automated systems now allow for highly accurate and efficient analysis of a wide variety of diagnostic types of digital images. Advanced fuzzy- and sparse-based multimodal digital imagery systems are quickly emerging as the next generation, helping improve the quality and speed of the diagnostic process across multiple healthcare settings. A significant benefit of these enhanced automated systems is the ability to extract substantially more information from multiple-spectral images, leveraging both their spatial and spectral features. Multispectral imaging is a technique for capturing images across specific sections of the electromagnetic spectrum, even outside the visible range, to provide a clearer, more detailed, and more complete representation of the object or tissue being examined. Fuzzy Logic is a method of dealing with imprecision and uncertainty in the available data. Fuzzy Logic is used in Medical Imaging via the Fuzzy Clustering Algorithm, which allows classification of different types of tissues or structures in an image based on their characteristics. Using the Fuzzy Logic method of image recognition, it has been possible to create an image recognition system with improved ability to handle the variation and noise found in images, compared to traditional methods. On the other hand, the Sparse Representation approach identifies and extracts the optimal features from the dataset, providing the most relevant features to describe the data and eliminating redundant ones.

When employed in image recognition, Sparse Representation allows selection of only the most relevant features during classification, enabling more accurate and efficient classification. Systems for multispectral recognition that combine the strengths of fuzzy logic and sparse representation are highly effective across several previously developed health-care-focused applications. When used as a diagnostic tool, fuzzy and sparse approaches for evaluating multispectral tumour tissue images provide more accurate, detailed assessments than either approach alone. The systems can identify very specific biomarker expressions within images, thereby supporting earlier diagnosis and treatment planning. Similarly, research combining multispectral imaging with fuzzy/sparse methods to aid in identifying abnormal features in brain images has been very successful across various types of neurological disorders. That is to say, multispectral imaging enables the system to detect very subtle changes in brain tissue that may be undetectable or very difficult to detect with conventional techniques. Combining this capability with the more powerful fuzzy and sparse algorithms available in these systems enables the system to provide significantly improved diagnostic accuracy and reliability compared to historically used methods for diagnosing neurological disorders. Additionally, robust fuzzy and sparse-based multispectral imaging systems have been implemented in surgical guidance and monitoring, where real-time multispectral image capture of anatomical tissues and structures during surgery provides surgeons with improved guidance, enhanced by greater accuracy and precision.

3.3. Identified Issues

- A primary technical challenge in multispectral digital image recognition systems is reducing the impact of noise, which can originate from environmental factors or the imaging method. Robust methods for filtering/removing noise are required to achieve the accuracy and reliability of the recognition process.
- The application of fuzzy logic provides a means of working with uncertain and imprecise input. Fuzzy logic will play an important role in developing a robust multispectral digital image recognition system, but implementing fuzzy logic algorithms can be complex and time-consuming.
- Sparse coding is a technique for compressing data into a compact representation using a few basic components. Sparse coding methods can be useful for reducing the dimensionality of input data in multispectral digital image recognition systems and for improving the efficiency of processing large amounts of data.
- Dimensionality reduction techniques, such as principal component analysis, can reduce the feature count of a multispectral digital image, enabling more efficient computation and analysis while retaining most or all of the dataset's critical information.

4. Proposed Model

The input image is a key element in most image processing systems. It serves as the basis for creating features and for creating other images. Input images are typically represented as large arrays of pixels, each with an associated brightness value at a specific location. Figure 6 depicts images generated by the developed model and includes an example demonstrating how such a model can be built, along with an example of the resulting output.

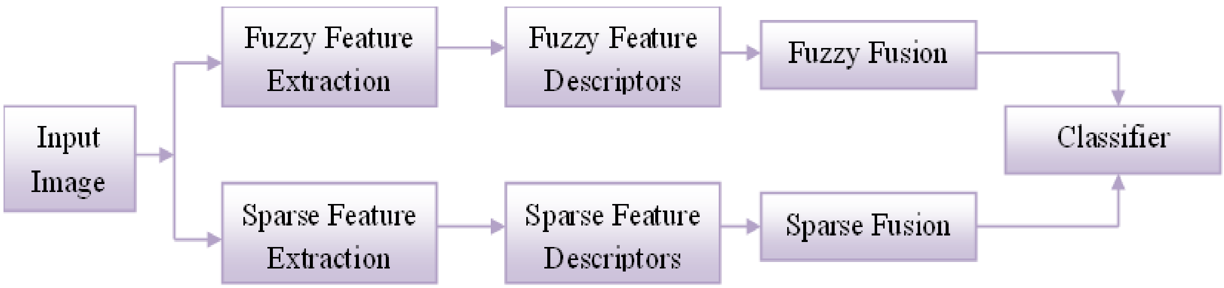

Figure 6: Construction of the proposed model

The fuzzy aspect of any image processing system involves isolating fuzzy characteristics from the source image, a process called fuzzy feature extraction. This method summarises the details of the original image using fuzzy concepts. Fuzzy logic, a mathematical scheme used for managing imprecise and uncertain data, serves as the basis for fuzzy feature extraction:

$$\sum_{i=1}^{n} \sum_{j=1}^{m} \delta(i, j) \tag{1}$$

Through the fuzzy feature extraction method, researchers will identify and summarize all the fuzzy features within an image based on what vague/ ambiguous data may be seen in a given image (real world), therefore identifying how they interact with each other:

$$\sqrt{(a_1 - a_2)^2 - (b_1 - b_2)^2} \tag{2}$$

Colour, texture, shape, and other key attributes of images will fall under the family of fuzzy features, as will any other characteristics of images:

$$\sqrt{(a_2 - a_1)^2 - (b_2 - b_1)^2} \tag{3}$$

Though there is a large volume of fuzzy feature extraction techniques on the web, these techniques usually involve taking the pixel values of an image and classifying them into fuzzy sets, then combining and summarising those sets, to yield a more compact and abstract representation of the image that can be processed more efficiently:

$$\sum_{i=0}^{L-1} pi(i) \tag{4}$$

It allows for a compact, abstract image representation that is easier to handle and evaluate. Fuzzy feature descriptors are numerical representations of the fuzzy features extracted from the original (input) image:

$$\sum_{i=0}^{L-1} (i - \mu)^2 p(i) \tag{5}$$

These descriptors summarize an image's characteristics. They are utilized as input into the next stage of the image processing system. The calculations for the fuzzy feature descriptors are based on numerous different mathematical operations associated with the various fuzzy features that were extracted from the original image:

$$1 - \left(\frac{1}{1} + \sigma^2\right) \tag{6}$$

Combining all fuzzy feature descriptors into one fuzzy representation is called Fuzzy Fusion. Since numerous degrees of fuzzy features contain conflicting or redundant information, it is important to perform the fuzzy fusion step:

$$\sum_{i=0}^{L-1} (i - \mu)^2 p(i) \tag{7}$$

When the fuzzy feature descriptors have been fused into one fuzzy representation, our representation of the input will contain more information about the input image than if researchers had used only one fuzzy feature descriptor or even developed two fuzzy feature descriptors independently from one another. This will lower the chance of any misclassifications taking place in subsequent processes:

$$\sigma^{-3} \sum_{i=0}^{L-1} (i - \mu)^3 p(i) \tag{8}$$

Extracting Sparse Features from an Image is a phase of the image processing workflow that is designed to represent the most significant parts of an image accurately and distinctively:

$$\sum_{i=0}^{L-1} p(i)^2 = \frac{\left(-\sum_i \sum_j p(i,j) \cdot \log(p(i,j)) - \left(-\sum_i \sum_j p(i,j) \cdot \log\left(p_x(i) p_y(j)\right)\right)\right)}{\max - \sum_i p_x(i) \cdot \log(p_x(i)), - \sum_i p_y(i) \cdot \log\left(p_y(i)\right)} \tag{9}$$

Sparse features are typically found near one another in an input image, while fuzzy features can be found throughout the image. Examples of sparse features include edges, corners, and lines; they tend to be geometric in shape and generally consist of multiple straight-line segments:

$$\sum_{i=0}^{L-1} p(i)^2 = \left(1 - \exp\left[-2\left(\left(-\sum_i \sum_j p_x(i) p_y(j) \cdot \log\left(p_x(i) p_y(j)\right) - \left(-\sum_i \sum_j p(i,j) \cdot \log\left(p(i,j)\right)\right)\right)\right)\right]\right)^{\frac{1}{2}} \tag{10}$$

The method for extracting sparse features consists of locating and identifying points or areas defined by them. After locating sparse features, descriptors are used to characterize them. There are many different methods available for calculating descriptors for sparse features, including gradient computation, filtering image data (filtering), and other image-processing techniques that will lead to calculating a compact, unique set of features for each class of images. The last phase of integrating sparse features into a single, comprehensive description of all features is called sparse fusion:

$$\frac{\partial O}{\partial P} * \frac{\partial P}{\partial O} = 1 \tag{11}$$

$$\frac{df}{de} = \left(E * \frac{dF}{de}\right) + \left(F * \frac{dE}{de}\right) \tag{12}$$

$$\frac{\partial p}{\partial o} = \left(O * \frac{\partial P}{\partial o}\right) + \left(N * \frac{\partial O}{\partial p}\right) \tag{13}$$

$$\frac{df}{de} = \left(e^e * \frac{d}{de}\sin E f\right) + \left(\sin E f * \frac{d}{de}(e^e)\right) \tag{14}$$

Fusing these features will provide a comprehensive representation, as they each capture different aspects of the input image. Sparse Fusion Techniques combine descriptors by mathematical methods (averaging, weighting, scaling, concatenation, etc.). The final part of the image processing system is the Classifier, which uses a mathematical model to classify images based on extracted features. The Classifier uses the fused feature inputs from the fuzzy and sparse phases to produce a class label. Multiple types of classifiers can be used depending on the application, including neural networks, support vector machines, and decision trees. The input image is the first step in any image processing system, and during the fuzzy and sparse phases, image features are extracted using fuzzy and sparse feature extraction techniques. These feature descriptors are merged to create a comprehensive description of the original input image, which is then used as input to the Classifier, which then uses the data to generate the proper classification of the input image into one or more classes. The process of extracting, fusing, and classifying features enables much more accurate and robust image processing across many applications.

4.1. Fuzzy Image Recognition

PkA and PkB are two separate pixel blocks within an image that have been vectorized for spatially grouping pixels into smaller blocks. Vectorization enables greater analytical efficiency in analysing and developing images by preserving spatially related pixels. Moreover, to systematically address the broad random variation in pixel values within a vector block, fuzzy coding is used to transform all pixel values using fuzzy logic. Fuzzy coding assigns a degree of membership to each pixel value for each category or group of pixels to which it belongs, accommodating for the uncertainty and variation inherent in all pixels of an image. For remote sensing analysis to collect geographical data and monitor environmental change, the types of images typically used include LNMS and LNSAR. After pixel block vectorization (PkA and PkB), the vector blocks are re-coded (VkA and VkB) to produce vectors for subsequent analysis. Vectors akA and akB denote the fuzzy coefficients related to the degree of membership of each pixel contained within each pixel block. To calculate fuzzy coefficients, mathematical formulas are applied to obtain fuzzy coefficients with accuracy based on the spatial relationships among all pixels in the pixel block, and the fuzzy representation of this concept is illustrated in Figure 7.

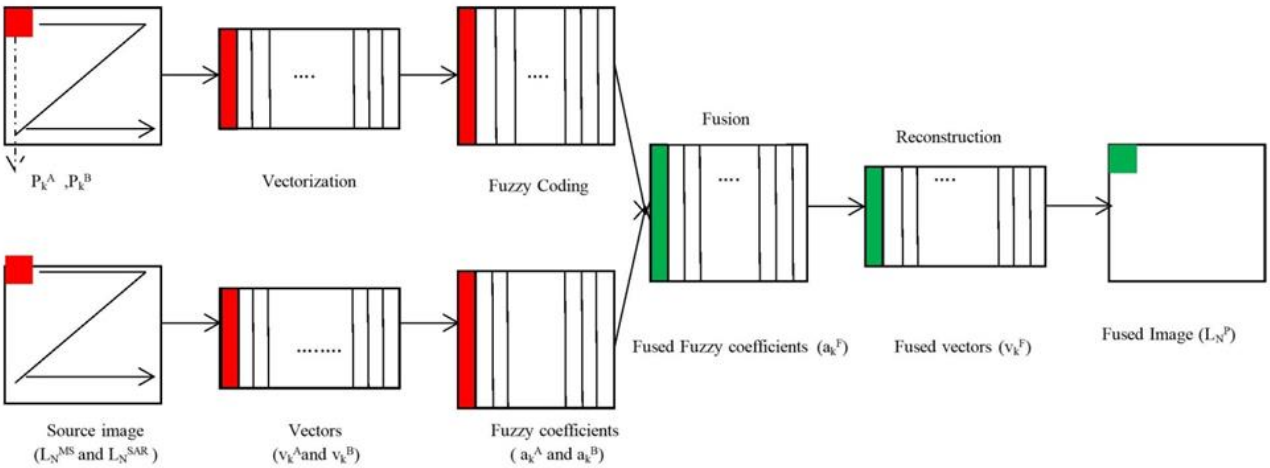

Figure 7: Fuzzy representation

Creating a detailed visual can be accomplished through combining the image data using a technique called fusion, which incorporates all the fuzzy coefficients of pixel intensity values into one combined fuzzy coefficient set:

$$\left(\frac{E*E_e}{F_e}\right) = \frac{1}{2}E * f_e^2 \tag{15}$$

The fused fuzzy coefficients contain the combined pixel information of both blocks, resulting in an improved visual of the original image:

$$\partial p'' = \lim_{p\to 0}\left(\frac{\partial p(o+p) - \partial p(o)}{\partial o}\right) \tag{16}$$

After all fg fuzzy coefficients are merged, the new fused vectors allow for a new image to be generated through reconstruction based on these new coefficients:

$$\partial p' = \lim_{p \to 0} \left(\frac{\partial o^{p+o} - \partial p^{o}}{\partial o} \right) \quad (17)$$

The fused version of the image (LNP) shows the synthesis of the two original blocks to generate the best evaluation of the source image by fusing both images:

$$\partial p'' = \lim_{p \to 0} \left(\frac{\partial (p^{o} * p^{o}) - \partial p^{o}}{\partial o} \right) \quad (18)$$

In addition to using vectorization with fuzzy encoding and fusion techniques, finer details can be provided of the source image using these fusion methods:

$$f'' = g^{e} * \lim_{e \to 0} \left(\frac{(g^{f} - 1)}{f} \right) \quad (19)$$

Fusing these various techniques enables remote sensing to process and analyze large amounts of spatial information and to provide accurate, detailed information about the area being monitored. A fused image created from multiple image blocks provides the user with an accurate and complete representation of the area under study.

4.2. Sparse Image Recognition

An image processing method that represents an image as a linear combination of a set of basic elements, or atoms, from a given dictionary is known as sparse representation. Sparsity refers to how many components of the signal are non-zero or close to zero. To create a sparse representation of an image, the creation of a dictionary of atoms (the basis of the sparse representation) and the multi-resolution decomposition of an image into its component bands (the different levels of a multi-resolution representation) must be done.

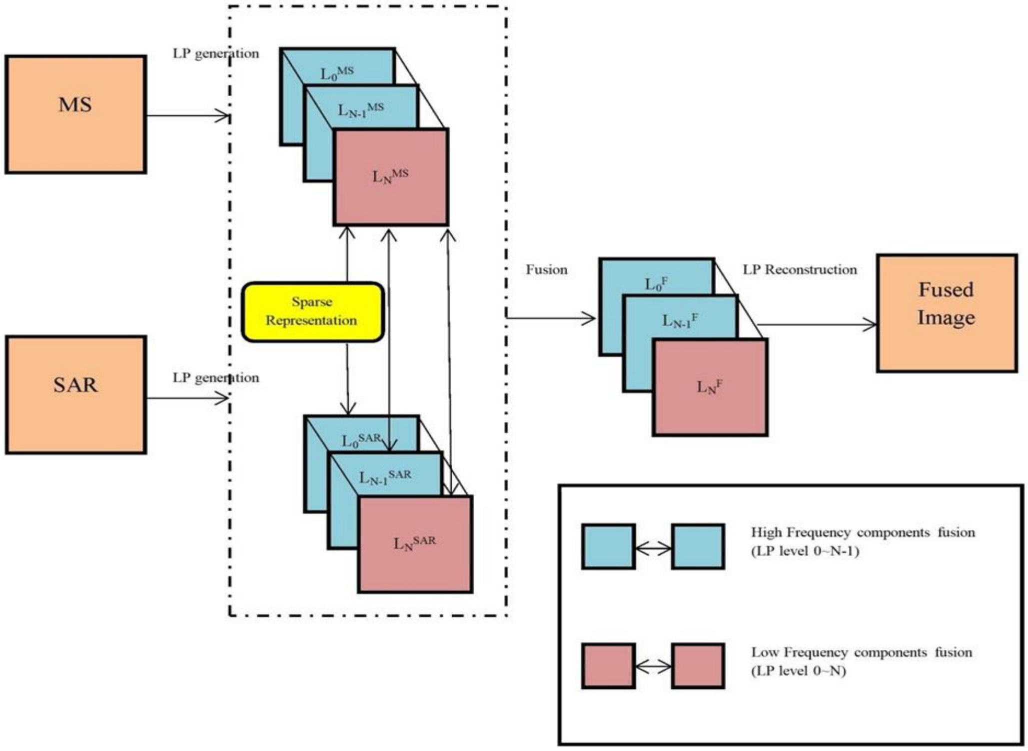

Figure 8: Sparse representation

The creation of the dictionary is referred to as MS Generation. The atoms selected can either come from a predefined dictionary or be learned from the image using dictionary-learning techniques. The multi-resolution decomposition of an image is referred to as LP Generation. The multi-resolution decomposition is performed by dividing an image into several levels (or layers) representing different frequency bands. The first level of the decomposition (Level 0, L0) contains the high-frequency components of the image, while the subsequent levels contain progressively lower frequency components. Thus, L0 is referred to as L0MS and L0LP, respectively, and the sparse representations are shown in Figure 8. The MS and LP for each LN level 1 include the MS and LP on the graph interface, LN-1 for both. The only difference is the density of the lowest expression; each of these images only shows the lowest density of items, which makes them both one image rather than two:

$$f_e^2 = \left(\frac{E * E_e}{F_e}\right) * \frac{2}{E} \tag{20}$$

Once the MS and LP images have been produced, the result is a sparse image representation achieved through compressive sensing:

$$\partial p = \lim_{o \to 0}\left(\frac{\partial p^o * \partial(p^o - 1)}{\partial o}\right) \tag{21}$$

The reconstruction of the original image takes place through the use of fusion techniques applied to the sparse representations of the images:

$$\partial o'' = \partial p^o * \lim_{o \to 0}\left(\frac{\partial(p^o - 1)}{\partial p}\right) \tag{22}$$

The fusion technique combines the high- and low-frequency components at the same level of decomposition (LP) to yield a single image that represents their combination. The result is a complete and faithful representation of the input images based on their sparse representations:

$$\partial o = \partial p^o * \ln(\,p) \tag{23}$$

$$\left(\frac{\partial O * \partial O_o}{\partial P_o}\right) = \frac{1}{2}\partial O * \partial p_o^2 \tag{24}$$

The format used to represent this process includes L0F and LN-1F, where "LN" means to perform multiple frequency level fusions for multiple frequency level images:

$$f'' = \lim_{e \to 0}\left(\frac{(g^e * g^f) - g^e}{f}\right) \tag{25}$$

Combining images at different frequencies yields a single image that contains both high and low frequencies, thereby providing a fuller representation of the original image:

$$\partial p_o^2 = \left(\frac{\partial O * \partial O_o}{\partial P_o}\right) * \frac{2}{\partial o} \tag{26}$$

If the input representation is sparse, the combined image used to create it is approximated to have the same characteristics. Therefore, the combined picture can be used to create a picture that has these same features:

$$\partial p_o^2 = \left(\frac{2 * \partial O_p}{\partial P_o}\right) \tag{27}$$

An inverse multi-scale decomposition process reconstructs the original image during the LPS reconstruction process:

$$\text{Where, } o = \left(\frac{\partial P_o}{\partial O_p^2}\right) \tag{28}$$

$$\partial o_p^2 = 2 * \partial o * \partial O_p \tag{29}$$

The accurate representation of images by using the different types of Representation methods is possible through the Fusion of several Images based on their high and low frequency components, creating the Final Representation of the Image:

$$f_e^2 = \left(\frac{2 * E_e}{F_e}\right) \tag{30}$$

Where, $g = \left(\frac{E_e}{F_e^2}\right)$; (31)

By using Sparse and Multi-Strategy approaches to generate the Combined MS and Combined LPS Images, researchers have created a unique and effective method for providing a Complete and Accurate Representation of an Image, with applications in areas such as Imaging Processing, Data Compression, and Pattern Recognition.

4.3. Proposed Algorithm

Two coordinates (A and B) are input to this process as a coordinate pair (x, y). The purpose of this process is to calculate two different outputs: Q*FIR and R*FIR. To start, the values of points A and B are placed into an Input. An IMG image file is created to create the foundation for subsequent processing. Afterwards, the input is segmented into manageable parts for easier analysis and processing. Using the x and y coordinates of points A and B, segments are created of the image. The segment sizes are determined by the values of n1 and n2, which can be changed or set appropriately. The proposed algorithm, along with all supporting documentation, is included in the following algorithm: 1.

Algorithm 1: Proposed Image Recognition Algorithm	
Input: A (x,y), B	
Output: Q^*_{FIR}, R^*_{FIR}	
Step 1	INITIALIZE_Input.IMG (a(x));
Step 2	Partition.Input ( );
Step 3	for x = 1 to n_1
Step 4	for y = 1 to n_2
Step 5	SEGMENT_IMG (a(x));
Step 6	UPDATE_Centroid ( );
Step 7	ESTIMATE_IMG (a(x));
Step 8	UPDATE_Partition.Matrix;
Step 9	END
Step 10	END

Processing each image segment occurs through a series of discrete steps in the software application. Initially, it will create an isolated version of the selected portion of the image identified as SEGMENT_IMG. Creating an isolated instance of a segment allows the application to focus solely on a small section of the overall image. The next step in the procedure is to calculate the centroid of the SEGMENT_IMG using the coordinates of points A & B. A centroid is the centre point of an object; it serves as a common reference point for decision-making during subsequent processing of the same segment. After calculating the segment's centroid using this method, the software application estimates its elements using a dedicated estimation method. Using points, A & B, along with the current partitioned matrix and centroid, the application will then create an approximation of the element values for that segment, which will eventually be placed in the software application's final output data file. Once the segmentation estimation has been created, the updated matching matrix, which now includes the estimated element values, will serve as the basis for the next iteration, processing all segments in the original image until every segment has been processed. The estimated values and original matrix element values will be utilised to generate both the Q*FIR and R*FIR outputs from this automated image processor. Estimated values of a segment used to provide useful information about the image, highlighting a pattern, shape, and change in the intensity (colour and intensity) processed by taking a set of coordinates (i.e., point A and point B) and dividing it into smaller segments, recalculating the centroid of the segment, estimating the estimated value of each segment, producing two outputs of the estimated values. Possible uses include image processing or analysis. Can be customised by changing n1 and n2, or by choosing a different estimation algorithm.

5. Conclusion

This research demonstrates that using these systems can provide an opportunity to significantly augment and refine how healthcare diagnosis and treatment are performed by providing a workable framework for developing methods using Fuzzy and Sparse techniques to develop multispectral imaging systems for improved accuracy in diagnosing and treating diseases. In multispectral imaging systems, one of the most significant advantages is the ability to extract and analyse large amounts of data across multiple spectral bands, which can then be used to build a better understanding of the underlying image composition. This is particularly useful when determining subtle differences between tissues, such as colour or texture. Additionally, incorporating fuzzy logic into this process enables the system to accommodate the inherent ambiguity and uncertainty of different data types. The system is therefore better able to adapt to the inherent variability of multispectral imaging data. The research illustrates how sparse representation of complex image data results in a dramatic reduction in dimensionality, facilitating more efficient and accurate computations when analysing images. In the health care environment, this feature is extremely important because timely, accurate intervention significantly improves patient outcomes. The use of fuzzy and sparse techniques in conjunction with multispectral image recognition systems not only helps minimise patient risk and discomfort, but also reduces the number of invasive (biopsy) procedures required.

As a result, fewer procedures will require fewer resources, leading to cost savings for patients and more invasive treatment options. In addition, one of the primary contributions of this paper is to establish how fuzzy and sparse processing techniques can be integrated with machine learning and deep learning methodologies to create a new class of systems that automatically learn from new data, which in turn will result in improved efficiency and accuracy of the multispectral imaging processes. Another point that must be emphasised is that the overall robustness of any multispectral imaging system depends heavily on the quantity and quality of the training data used to build the system. Therefore, every effort must be made to acquire a broad, representative training dataset for the development of multispectral imaging systems. Data gathered from the research indicate that fuzzy and sparse multispectral imaging systems applied to the field of medical imaging have the potential to greatly enhance health-related outcomes; nevertheless, future research and development on the integration of these systems into health care systems, the optimization of associated algorithms, and continued improvement of image quality will drive the development and effectiveness of these technologies. Continued research and development of fuzzy and sparse multispectral imaging systems will result in major changes in the diagnosis and treatment of disease, thereby improving health care outcomes and enhancing service delivery.

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