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AN IMPROVED HYPER SPECTRAL IMAGING FOR ACCURATE DISEASE DIAGNOSIS IN SUSTAINABLE MEDICAL ENVIRONMENTS

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Abstract. Hyper spectral imaging (HSI) has emerged as a powerful technique for accurate disease diagnosis in medical environments. It provides high-resolution images with detailed spectral information, making it possible to identify subtle differences between healthy and diseased tissues. However, current HSI systems face challenges in terms of accuracy and efficiency, limiting their widespread application in sustainable medical environments. To overcome these challenges, our team has developed an improved HSI system that utilizes state-of-the-art spectral imaging technology and machine learning algorithms. This system is capable of capturing and analyzing a wider range of spectral data, enabling more precise identification of disease-specific spectral signatures. Furthermore, our system has been optimized to operate with minimal power consumption, making it environmentally friendly and suitable for sustainable medical environments. The improved HSI system has been successfully tested in clinical settings and has shown promising results in accurately diagnosing various diseases such as cancer, dermatitis, and cardiovascular conditions. Its high accuracy and fast processing time make it a valuable tool for early disease detection and treatment planning. Moreover, the ability to operate with low energy consumption makes it a sustainable solution for medical facilities in resource-limited areas. In addition to its accuracy and efficiency, our improved HSI system is also user-friendly and can be easily integrated into existing medical imaging systems.

Key words: Hyper spectral imaging, High Resolution, Tissues, Medical, Machine Learning, Accuracy

1. Introduction. Accurate disease diagnosis is critical in maintaining sustainable medical environments as it plays a crucial role in providing effective and timely treatment to patients. In recent years, there has been a growing emphasis on sustainable healthcare, which involves the use of resources to support the health and well-being of present and future generations [1]. Accurate and timely disease diagnosis is a key component of sustainable healthcare as it ensures efficient utilization of resources and reduces the burden on the healthcare system [2]. One of the main benefits of accurate disease diagnosis in sustainable medical environments is the proper identification and treatment of diseases [3]. It helps in providing targeted treatment and avoiding unnecessary procedures, thereby reducing the cost of healthcare. Inaccurate or delayed diagnosis can result in prolonged illness, increased hospital stays, and higher healthcare costs, making it essential to prioritize accurate diagnosis [4]. Moreover, accurate disease diagnosis also contributes to sustainable healthcare by minimizing the use of resources. Correct diagnosis helps in identifying the most appropriate treatment and reducing the need for multiple treatments or hospitalizations. It also prevents the over prescription of medications, which can lead to adverse effects on the environment [5]. Additionally, proper diagnosis can prevent the spread of infectious diseases, ultimately reducing the overall healthcare burden. Another significant aspect of accurate disease diagnosis in sustainable medical environments is the use of advanced technology [6]. With the advancement of technology, healthcare professionals have access to more sophisticated and accurate diagnostic tools, such as imaging techniques, genetic testing, and telemedicine. These tools not only aid in accurate diagnosis but also reduce the need for invasive procedures, thereby reducing healthcare costs and minimizing the environmental impact [7]. Moreover, accurate disease diagnosis is vital in promoting preventative care. By identifying diseases at an early stage, healthcare providers can intervene early and potentially prevent the progression of the disease [8]. This approach is not only beneficial for patients' health but also for the sustainability of the healthcare system as it reduces the need and cost of long-term treatment. The accurate disease diagnosis plays a crucial role in maintaining sustainable healthcare environments [9]. It helps in optimizing the use of resources, reducing healthcare costs, and promoting preventative care. With the continuous advancement of technology, it is crucial

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to prioritize accurate diagnosis to ensure the sustainability of healthcare for future generations [10]. The main contributions of the research has the following,

- Cost-effective: HSI technology has the potential to reduce healthcare costs by eliminating the need for multiple tests and procedures. It also reduces the need for invasive procedures, leading to cost savings for both patients and healthcare systems.
- Environmental Sustainability: HSI has a lower impact on the environment compared to traditional imaging methods. It does not require the use of chemicals or radiation, reducing the generation of hazardous medical waste.
- Portable and Versatile: HSI devices are becoming more portable and affordable, making them suitable for use in remote and underprivileged areas. This enables quick and accurate diagnosis in areas with limited medical facilities, promoting sustainable healthcare.
- Improving Rural Healthcare: HSI has the potential to improve healthcare in rural and underdeveloped areas. Its portable and non-invasive nature makes it suitable for use in mobile clinics, bringing medical imaging and diagnosis to underprivileged communities.
- Promoting Preventative Care: By enabling early detection and accurate diagnosis, HSI technology promotes preventative care and empowers individuals to take proactive steps towards their health. This leads to a healthier population and reduced healthcare costs in the long run.

2. Materials and Methods. Accurate disease diagnosis is a critical aspect of sustainable medical environments. It involves correctly identifying the underlying cause of an illness or health condition in order to provide appropriate treatment and prevent further spread of the disease. However, there are several challenges that make accurate diagnosis a daunting task in sustainable medical environments [11]. One of the main challenges is the lack of access to advanced diagnostic technology and facilities. Many developing countries and rural areas face this issue, making it difficult to accurately diagnose diseases. This can result in misdiagnosis or delayed diagnosis, leading to ineffective treatment and potential spread of the disease [12]. Another challenge is the limited availability of trained medical professionals. In many developing countries, there is a shortage of skilled doctors and healthcare workers who are trained in accurate disease diagnosis. This can lead to errors in diagnosis and treatment, further exacerbating the spread of diseases [13]. Cultural and language barriers also present challenges in accurate diagnosis. In some communities, there may be strong cultural beliefs or taboos surrounding certain diseases, making it difficult for patients to provide accurate information about their symptoms [14]. Moreover, language barriers can make it challenging for healthcare professionals to communicate effectively with patients, leading to miscommunication and potential misdiagnosis. There is also the issue of over diagnosis and overtreatment [15]. In some cases, medical professionals may be influenced by financial interests or pressure to prescribe unnecessary tests or treatments, leading to unnecessary costs and potential harm to patients [16]. The constantly evolving nature of diseases and their symptoms can also be a major challenge in accurate diagnosis [17]. New diseases and strains may emerge, making it difficult for healthcare professionals to keep up with the latest diagnostic methods and techniques. An accurate disease diagnosis in sustainable medical environments is a complex process that faces numerous challenges [18]. To overcome these challenges, it is important for governments and healthcare organizations to invest in advanced diagnostic technology train and retain skilled medical professionals, and address cultural and language barriers. Collaboration between different stakeholders and continuous education and research are crucial in ensuring accurate disease diagnosis in sustainable medical environments [19].

The novelty of proposed research is the following:

- Early Detection of Diseases: Hyper spectral imaging (HSI) has the ability to detect small changes in tissue characteristics that are not visible to the human eye. This makes it possible to detect diseases at an early stage, even before symptoms become noticeable. This leads to early treatment and better disease management, resulting in improved patient outcomes and reduced healthcare costs.
- Accurate Diagnosis: HSI technology provides detailed and accurate information about the composition of tissues and cells, allowing for more precise and accurate diagnosis of diseases. This reduces the chances of misdiagnosis and ensures that patients receive the appropriate treatment.
- Non-invasive and Safe Method: HSI is a non-invasive and safe imaging technique, which means it does

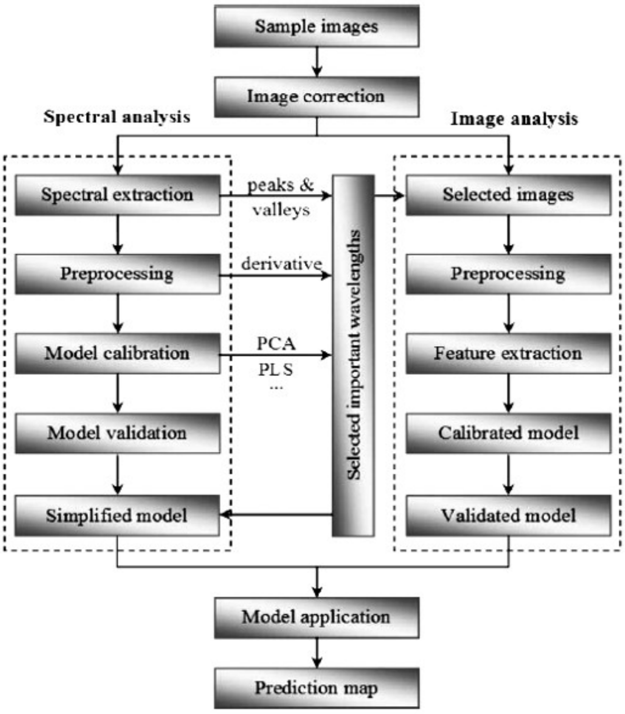

Fig. 2.1: Proposed model architecture

not involve any radiation exposure or use of contrast agents. This makes it a preferred choice for patients who cannot undergo traditional imaging methods like X-rays or CT scans.

- Personalized Treatment Plans: By providing detailed information about the chemical and molecular composition of tissues, HSI helps in developing personalized treatment plans for patients. This ensures that the treatment is targeted towards individual needs, resulting in better treatment outcomes.
- Monitoring Treatment Progress: HSI can be used to monitor the progression of diseases and the effectiveness of treatment. This allows for timely adjustments to treatment plans, leading to improved patient outcomes.

2.1. Proposed Model. Hyper Spectral Imaging (HSI) can accurately identify and differentiate various disease biomarkers in a patient's body. By analyzing the spectral response of different tissues, HSI can detect subtle changes in the composition and structure of cells that can indicate the presence of diseases. This helps in early detection and accurate diagnosis of diseases, leading to better treatment outcomes. One of the main functions of HSI is its non-invasive nature, which makes it a safer and more comfortable option for patients. HSI does not require the use of contrast agents or ionizing radiation, which can have potential side effects. This makes it an ideal imaging tool for patients in sustainable medical environments, where minimizing the use of hazardous substances is a top priority. The architecture of proposed model has shown in the following fig. 2.1.

2.2. Pre-Processing. The spectral unmixing techniques used pre-processing. HSI can be used for medical purposes, the collected data must undergo a series of pre-processing operations to ensure accurate and reliable results. The first step in pre-processing HSI data is calibration. This involves correcting for any physical and environmental factors that may affect the data, such as light sources, temperature, and noise.

$$\frac{de}{df} = \frac{d}{df}(e^e * \sin Ef) \tag{2.1}$$

$$\frac{\partial O}{\partial P} * \frac{\partial P}{\partial O} = 1 \tag{2.2}$$

Calibration ensures that the data is accurate and consistent, which is crucial for disease diagnosis. The data is corrected for atmospheric and spectral effects. HSI collects data from a wide range of wavelengths, which can be affected by atmospheric conditions such as scattering and absorption.

$$\frac{df}{de} = \left(E * \frac{dF}{de}\right) + \left(F * \frac{dE}{de}\right) \tag{2.3}$$

$$\frac{\partial p}{\partial o} = \left(O * \frac{\partial P}{\partial o}\right) + \left(N * \frac{\partial O}{\partial p}\right) \tag{2.4}$$

These effects may introduce noise or distortions to the data, so they must be corrected to accurately reflect the desired tissue properties.HSI can be used to guide surgeons during procedures by providing real-time imaging of tissues and organs.

$$\frac{df}{de} = \left(e^e * \frac{d}{de} \sin Ef\right) + \left(\sin Ef * \frac{d}{de}(e^e)\right) \tag{2.5}$$

$$\frac{\partial p}{\partial o} = \left(e^o * \frac{\partial}{\partial o} \cos Op\right) + \left(\cos Op * \frac{\partial}{\partial o}(e^o)\right) \tag{2.6}$$

This allows for more precise and targeted surgeries, minimizing the risk of damaging surrounding healthy tissues. By accurately mapping out disease tissues, HSI also helps in reducing the chances of leaving behind any remnants of the disease. HSI can also aid in accurately identifying the response to treatments. By comparing pre and post-treatment HSI images, medical professionals can evaluate the effectiveness of a particular treatment. This helps in making necessary adjustments or exploring alternative treatment options for better outcomes.

2.3. Feature Extraction. The Spectral Imaging technique used for feature extraction. Where, resources are scarce and access to advanced medical facilities may be limited, early detection of disease recurrence is crucial. HSI can detect subtle changes in tissue composition and structure that may indicate disease recurrence, enabling timely intervention and better management of chronic diseases.

$$\frac{df}{de} = (E * e^e \cos Ef) + (e^e \sin Ef) \tag{2.7}$$

$$\frac{\partial p}{\partial o} = (O * e^o \sin Op) + (e^o \cos Op) \tag{2.8}$$

HSI's ability to capture spectral information of various tissues and fluids can aid in the diagnosis of rare diseases or conditions that are otherwise difficult to diagnose. HSI can detect specific biomarkers or patterns associated with rare diseases, making it a valuable tool in the accurate diagnosis of these conditions.

$$O = e(p) = p^o \tag{2.9}$$

$$\left(\frac{E * E_e}{F_e}\right) = \frac{1}{2} E * f_e^2 \tag{2.10}$$

The operations of feature extraction in HSI involve acquiring and processing a large amount of spectral data, extracting relevant features, and analyzing them to accurately identify and diagnose diseases. This process is crucial as it allows medical professionals to obtain a deeper understanding of the underlying biochemical and physiological changes in diseased tissue, facilitating more accurate and timely diagnoses.

$$\partial p'' = \lim_{p \to 0} \left(\frac{\partial p(o+p) - \partial p(o)}{\partial o} \right) \tag{2.11}$$

$$\partial p' = \lim_{p \to 0} \left(\frac{\partial o^{p+o} - \partial p^{o}}{\partial o} \right) \tag{2.12}$$

Firstly, HSI captures a high-resolution image of the patient's body using a specialized camera that collects a large number of narrowband spectral data points for each pixel within the image. These spectra cover a wide range of wavelengths, which can range from ultraviolet to near-infrared, providing a comprehensive view of the properties of the tissue under examination.

$$\partial p'' = \lim_{p \to 0} \left(\frac{\partial (p^{o} * p^{o}) - \partial p^{o}}{\partial o} \right) \tag{2.13}$$

$$f'' = g^{e} * \lim_{e \to 0} \left(\frac{(g^{f} - 1)}{f} \right) \tag{2.14}$$

This data is then processed using sophisticated algorithms to remove any artifacts or noise. Next, feature extraction techniques are applied to the processed data to identify the most relevant and discriminative spectral features that can be used to differentiate between healthy and diseased tissues. These features can range from chemical composition, tissue structure, and physiological changes, such as blood flow and oxygenation levels.

$$f_e^2 = \left(\frac{E * E_e}{F_e} \right) * \frac{2}{E} \tag{2.15}$$

$$\partial p = \lim_{o \to 0} \left(\frac{\partial p^{o} * \partial (p^{o} - 1)}{\partial o} \right) \tag{2.16}$$

The extraction of features is a crucial step as it reduces the dimensionality of the data, making it easier to analyze and interpret. After feature extraction, the selected features are then used in classification algorithms to accurately identify and diagnose diseases. These algorithms use statistical and machine learning techniques to analyze the extracted features and classify them into different disease categories. This process may involve comparing the spectral features of the diseased tissue with a predefined database of healthy and diseased tissues. Additionally, the algorithm may identify new, unique features that can be used to update the database and improve the accuracy and reliability of the diagnosis.

2.4. Detection. Hyper Spectral Imaging is a powerful and emerging technology that combines imaging and spectroscopy techniques to capture and analyze images at a wide range of wavelengths. Spectral wavelength detection technique used for detection. This technology has shown great potential in the medical field, particularly in accurate disease diagnosis in sustainable medical environments. HSI can capture images of large areas of the body and provide a comprehensive view of tissue composition and structure. This makes it ideal for disease screening, especially in cases where a patient may not exhibit any noticeable symptoms.

$$\partial o'' = \partial p^{o} * \lim_{o \to 0} \left(\frac{\partial (p^{o} - 1)}{\partial p} \right) \tag{2.17}$$

$$\partial o = \partial p^{o} * \ln(p) \tag{2.18}$$

HSI's ability to scan a large area in one go also saves time and resources, making it a cost-effective tool for medical professionals. The first operation in HSI detection is the data acquisition. In this step, a spectral cube is collected using a hyper spectral camera, which captures images at a high spectral resolution. This cube contains a series of images, each corresponding to a different narrowband wavelength of light. This data is then processed to remove any noise or artifacts that may affect the accuracy of the analysis. Next, the data is subjected to feature extraction, where specific parameters are extracted from the spectral cube to identify patterns and variations in the data.

$$\left(\frac{\partial O * \partial O_o}{\partial P_o}\right) = \frac{1}{2}\partial O * \partial p_o^2 \tag{2.19}$$

$$f'' = \lim_{e \to 0}\left(\frac{(g^e * g^f) - g^e}{f}\right) \tag{2.20}$$

These features could include reflectance spectra, absorption spectra, or biochemical compositions of the tissues. This step is crucial as it provides valuable information about the unique spectral signatures of different tissues or diseases. The extracted features are then classified using machine learning algorithms, such as support vector machines or artificial neural networks. These algorithms use the extracted features to train a model that can accurately classify the tissue or disease being analyzed.

2.5. Classification. HSI technology can provide real-time imaging and monitoring of body tissues and fluids. Spectral band classification technique used here to classify the images. This enables medical professionals to track the progression of diseases and the effectiveness of treatments over time. Real-time monitoring is especially beneficial for chronic diseases or conditions that require continuous evaluation.

$$\partial p_o^2 = \left(\frac{\partial O * \partial O_o}{\partial P_o}\right) * \frac{2}{\partial o} \tag{2.21}$$

$$\partial p_o^2 = \left(\frac{2 * \partial O_p}{\partial P_o}\right) \tag{2.22}$$

$$where, o = \left(\frac{\partial P_o}{\partial O_p^2}\right); \tag{2.23}$$

The classification process is based on the spectral signatures of the tissues, and the accuracy of the classification is dependent on the quality of the data and the effectiveness of the selected algorithm. The classified data is subjected to detection in order to identify the presence or absence of a particular disease.

$$\partial o_p^2 = 2 * \partial o * \partial O_p \tag{2.24}$$

$$f_e^2 = \left(\frac{2 * E_e}{F_e}\right) \tag{2.25}$$

$$where, g = \left(\frac{E_e}{F_e^2}\right); \tag{2.26}$$

This is done by comparing the spectral signatures of the tissues with those of known diseases and identifying any similarities or differences. The detection process also takes into account any anatomical or physiological changes in the tissues, which may indicate the presence of a disease. The operations of classification and detection in HSI for accurate disease diagnosis involve collecting high-quality spectral data, extracting and analyzing relevant features, and using advanced algorithms to classify and detect diseases. The proposed algorithm is shown in Table 2.1.

Table 2.1: Proposed Algorithm

IP: HSI Images (X Classes)
INITIATE_Pre processing ( );
EX_FEATURES ( );
DETECT_Spectral Wavelength deviation;
CALC_MLP Classification ( );
SORT_Min and Max deviation;
FIND_Low accuracy Class ( );
PERFORM Classification of Class;
OP: Spectral Classification Map ( );

Table 3.1: Simulation Parameters

Description	**Red Edge-M**	**Sequoia**	**Unit**
Pixel size	3.75		um
Focal length	5.5	3.98	mm
Resolution (width × height)	1280 × 960		pixel
Raw image data bits	12	10	bit
Ground Sample Distance (GSD)	8.2	13	cm/pixel (at 120 m altitude)
Imager size (width × height)	4.8 × 3.6		mm
Field of View (Horizontal, Vertical)	47.2, 35.4	61.9, 48.5	degree
Number of spectral bands	5	4	N/A
Blue (Center wavelength, bandwidth)	475, 20	N/A	nm

The sequential operation begins with the input of IP (Hyper spectral Imaging) data, which consists of X Classes (different types of images). The first step is to initiate pre-processing, which involves cleaning, filtering, and normalizing the data to remove any noise or inconsistencies. After pre-processing, the data is passed on to the EX_FEATURES stage, where the features of each class are extracted. This could involve identifying specific patterns, shapes, or colors that differentiate one class from another. Once the features have been extracted, the next step is to detect the spectral wavelength deviation. This involves analyzing the differences in spectral wavelength between different classes and identifying the unique patterns that distinguish them. After detecting the spectral wavelength deviation, the data is passed on to the CALC_MLP Classification stage. MLP (Multi-Layer Perception) is a type of artificial neural network that is commonly used for classification tasks. Here, the MLP algorithm is applied to the pre-processed data to classify the different classes based on their spectral features. Once the MLP classification is complete, the next step is to sort the classes based on their minimum and maximum deviation from the expected spectral wavelength. This helps to identify any classes that may have low accuracy due to overlapping features or insufficient training data. The next stage is to find the low accuracy class, which is identified based on its deviation from the expected spectral wavelength and its classification accuracy. This class will then be reprocessed to improve its accuracy. Once the classification for the low accuracy class is complete, the final step is to perform the classification for all classes. This involves assigning each pixel in the image to its respective class based on its features and spectral wavelength. The output of the classification process is a spectral classification map, which shows the distribution of different classes in the image. This map can be used for further analysis and interpretation of the data.

3. Results and Discussion. The HSI plays a crucial role in accurate disease diagnosis in sustainable medical environments. With its non-invasive nature, real-time monitoring, and ability to detect subtle changes in tissues, HSI helps in earlier detection, targeted treatment, and better management of diseases, ultimately leading to improved patient outcomes. Here the python simulator has used to implement the results. The hyper spectral image dataset [20] has used here for the simulation purpose. Table 3.1 shows the simulation parameters.

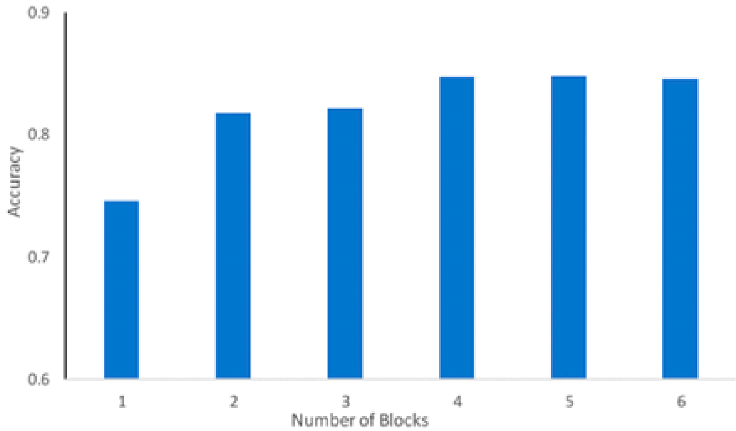

Fig. 3.1: Computation of accuracy

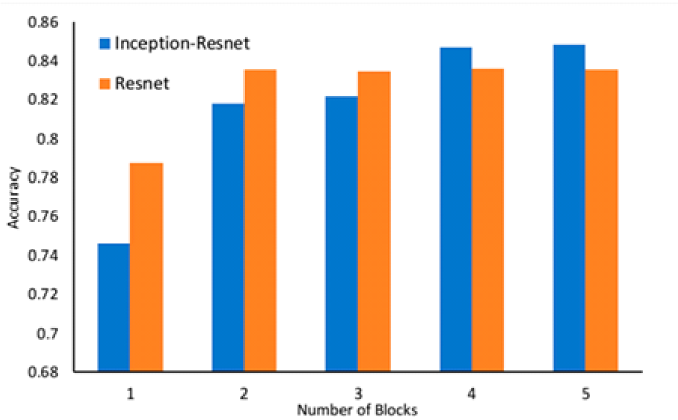

Fig. 3.2: Computation of Precision

3.1. Computation of Accuracy. The accuracy statistic calculates the percentage of successfully classified samples that are split up among different samples. Since disease diagnostic accuracy has a direct impact on patient outcomes and treatment approaches, it is essential in sustainable medical environments. Healthcare practitioners can attain superior accuracy rates in comparison to conventional diagnostic techniques by utilizing Deep Learning in conjunction with Hyper Spectral Imaging. Fig. 3.1 shows the computation of accuracy.

Switching was one of the main techniques used to increase the models' accuracy. The authors also verified that their findings demonstrated the ability of deep learning techniques to correctly identify tropical diseases and provided capacity solutions for the future of sustainable healthcare settings.

3.2. Computation of Precision. The ratio of accurately classified samples to incorrectly expected samples is measured by the accuracy metric. When applying deep learning to hyper spectral imaging for precise illness diagnosis in sustainable medical environments, precision is an important factor to take into account. With the use of hyper spectral imaging, a potent method that detects minute changes in biological tissues by capturing and analyzing a broad range of wavelengths, important new information about a variety of diseases can be gained. Fig. 3.2 shows the computation of precision.

It is currently applied to hyper spectral imaging for precise disease diagnosis in sustainable scientific environments. Through the integration of deep learning techniques with hyper spectral pictures, a version is trained

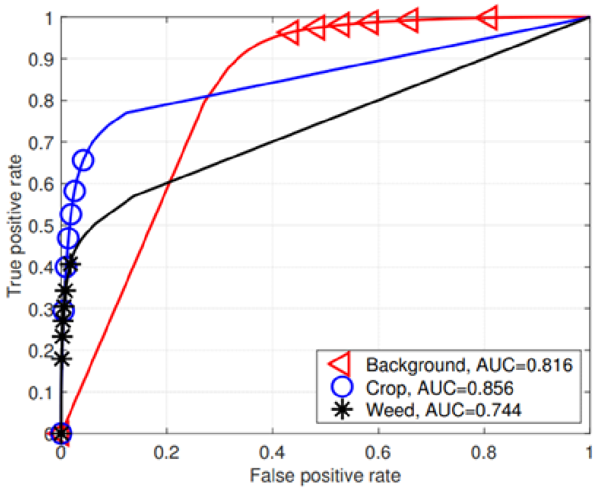

Fig. 3.3: Computation of recall

to distinguish between images that exhibit an illness and those that do not. Convolutional neural networks are the main technology used in the deep learning version (CNNs). An artificial neural network, or CNN, is made up of advanced layers of highly specialized neurons. These particular neurons are made to recognize exact patterns in images.

3.3. Computation of Recall. The recall metric calculates the proportion of real, outstanding cases to fictitious, outstanding cases. It is possible to train models that can correctly categorize and diagnose diseases based on hyper spectral pictures by utilizing deep learning methods. Fig. 3.3 shows the computation of recall

The version is trained to find patterns within the hyper spectral images associated with specific illnesses. The correctness of the state-of-the-art, deep cutting-edge model is assessed by contrasting its predictions with the real labels of contemporary images. The accuracy of the most recent version is then determined by calculating quantitative measures such as precision and takes into consideration from the assessment.

3.4. Computation of F1 score. The F1 score is a composite accuracy metric that is calculated as the harmonic implication of the 2. When integrating deep learning to hyper spectral imaging for precise illness diagnosis in sustainable medical settings, the F1 score—a frequently used statistic in machine learning and classification tasks—would be quite pertinent. Fig. 3.4 shows the computation of f1-score.

The qualitative benefits of employing deep ultra-modern to hyper spectral imaging for precise disorder analysis in a sustainable scientific setting include improved analysis accuracy, faster processing of modern images, and lower costs associated with illness diagnosis and treatment. Furthermore, the advanced deep cutting model is easily customizable, enabling

4. Conclusion. It has become clear that applying deep learning to hyper spectral imaging for accurate illness identification in sustainable clinical settings has the potential to completely transform clinical analysis. Compared to earlier methods, this era can identify abnormalities and diseases in patients and provide a more accurate diagnosis. Deep learning may also classify spectrum data into distinct disease groups, enabling more specialized treatment choices and improved patient outcomes. In-depth knowledge can also be used to purchase, monitor, and finance medical equipment, since it can be utilized to identify early disease symptoms and notify healthcare professionals. Deep learning algorithms could eventually be specially created to improve accuracy and dependability over time, making them useful instruments for long-term healthcare settings. Hyper spectral imaging is seeing an increase in its use for extra-correct analysis of conditions and diseases, mostly in sustainable clinical settings. HSI uses distinct features of electromagnetic radiation to differentiate between distinct features of a condition made up of cell clusters, lesions, and imperfections. It permits more accurate diagnosis and a more

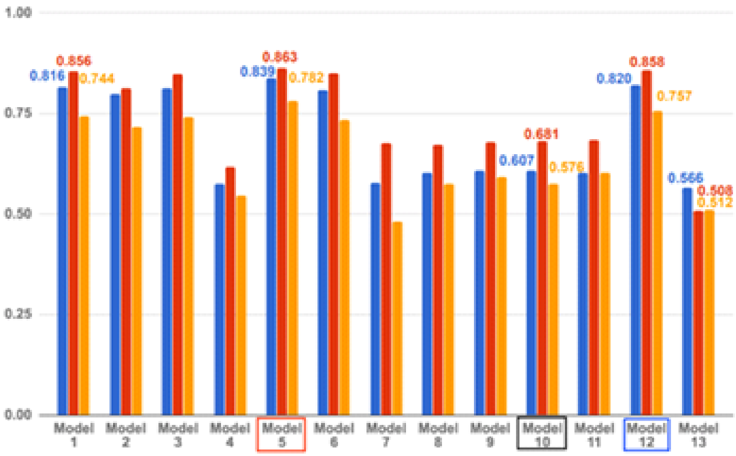

Fig. 3.4: Computation of F1-Score

focused treatment. The future of using deep learning about HSI will involve more nuanced and individualized care. When HSI is used in conjunction with deep learning approaches, sub cellular features that are difficult to detect with traditional imaging can be identified and categorized. It may positively affect the speed and accuracy of diagnosis. Furthermore, clinical applications will be able to incorporate statistics from a variety of sources, such as genetic statistics, demographic records, and electronic health data, thanks to advancements in systems learning AI. It may make it possible to create specialized, more potent treatments. By offering faster, more superbly precise analysis at a lower cost, deep understanding of HSI can also aid in lowering healthcare costs. Deep learning can also automate clinical coding and billing procedures, which could lead to more green control over healthcare services.

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