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A hybrid fused-KNN based intelligent model to access melanoma disease risk using indoor positioning system

Sushruta Mishra[1], Himansu Das[1]✉, Sunil Kumar Mohapatra[2], Surbhi Bhatia Khan[3,4]✉, Mohammad Alojail[5] & Mo Saraee[3]

The Indoor Positioning System (IPS) based technology involves the positioning system using sensors and actuators, where the Global Positioning System (GPS) lacks. The IPS system can be used in buildings, malls, parking lots and several other application domains. This system can also be useful in the healthcare centre as an assisting medium for medical professionals in the disease of the diagnosis task. This research work includes the development and implementation of an intelligent and automated IPS based model for melanoma disease detection using image sets. A new classification approach called Fused K-nearest neighbor (KNN) is applied in this study. The IPS based Fused-KNN is a fusion of three distinct folds in KNN (3-NN, 5-NN and 7-NN) where the model is developed using input samples from various sensory units while involving image optimization processes such as the image similarity index, image overlapping and image sampling which helps in refining raw melanoma images thereby extracting a combined image from the sensors. The IPS based Fused-KNN model used in the study obtained an accuracy of 97.8%, which is considerably more than the existing classifiers. The error rate is also least with this new model which is introduced. RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) value generated with the proposed IPS base Fused-KNN the model for melanoma detection was as low as 0.2476 and 0.542 respectively. An average mean value computed for accuracy, precision, recall and f-score were found to be 94.45%, 95.2%, 94.4% and 94.9% respectively when validated with 12 different cancer-based datasets. Hence the presented IPS based model can prove to be an efficient and intelligent predictive model for melanoma disease diagnosis, but also other cancer-based diseases in a faster and more reliable manner than existing models.

Keywords Indoor positioning system (IPS), Melanoma, K-nearest neighbor, Disease diagnosis, Global positioning system (GPS), Healthcare

The real-time location of objects is vital in critical fields like healthcare domain. Indoor positioning systems (IPS) can be used in medical space to assess various diseases. IPS systems involve sensors and navigation systems where GPS cannot work effectively. Our research work focuses on the detection of melanoma skin cancer based on the IPS system. Using an IPS based system, sensors are automatically used for analyzing patient input patterns. In our model, we used sensors such as CCD and CMOS and IR camera sensors as well as LIDAR for laser sampling. Images are processed by image processing methods such as image sampling and image restoration. Normalized cross correlation (NCC) algorithm was used in our model to detect similarity in camera and laser sample image patterns. If similarities are found, the image overlay method is used to obtain the final image, which is then processed to reduce image noise. Feature extraction is done after image optimization. In our study, we introduced a new classifier, based on IPS and the combination of three variants of KNN algorithm, called Fused-KNN model. This hybrid model classified the melanoma samples and the classification performance is extremely encouraging. Thus, it can be concluded that the proposed IPS based intelligent framework can be an effective tool for the accurate detection and classification of melanoma diagnoses.

[1]Kalinga Institute of Industrial Technology, Bhubaneswar, India. [2]Centurion University of Technology & Management, Bhubaneswar, India. [3]School of Science, Engineering and Environment, University of Salford, Salford, UK. [4]University Centre for Research and Development, Chandigarh University, Mohali, Punjab, India. [5]Management Information System Department, College of Business Administration, King Saud University, Riyadh, Saudi Arabia. ✉email: himanshufcs@kiit.ac.in; s.khan138@salford.ac.uk

In men, skin cancer is the most common and serious type of cancer[1]. Melanoma is a deadly type of skin cancer. The conventional method for diagnosing melanoma in today's era is biopsy[2]. Dermatologists frequently use subsequent dermatological photography of inflammation of the skin to identify or test up melanoma earlier. Nonetheless, spot scanning of the disease is used in developing current methods for early identification of melanoma. In marginal circumstances, overlooking variations in the lesion's form and timing could result in a misinterpretation[3]. Many disorders, including skin cancer, can be detected via pathological scanning. Given that digital pathology photos are frequently quite large—billions of pixels in size—automatic detection of aberrant cellular nuclei and how they are distributed across several tissue sections will enable evaluation thorough and prompt diagnosis.

In this research, we provide a deep learning-based method for segmenting melanoma areas from pathology pictures stained with hematite and immunoglobulin. This method involves first segmenting the picture's nucleus utilizing a deep-learning neural network. The melanoma area was then covered up with the divided nuclei. Based on the results of experiments, the suggested technique may achieve around 90% accuracy in nuclear identification and approximately 98% accuracy in melanoma identification. There is very little computational complexity in the suggested method[4]. Histopathology imaging is commonly utilized to detect disorders like skin cancer. Because computerized histopathology pictures are frequently quite big, in the millions of pixels range, the automatic detection of odd cell nuclei and their distribution across several sections of tissue allows for complete and speedy detection. This research presents a deep learning-based method for segmenting melanoma areas in hematology and eosin-stained histopathology images[5]. Vital characteristics of IPS are listed here, which is highlighted in Fig. 1.

- *Accuracy*: The Euclidean distance average between the approximate position and actual position determines the overall accuracy of the system. The biggest challenge for the IPS is accuracy.
- *Coverage & Scalability*: Along with accuracy, the coverage of the IPS network is mandatory and as well as the scope of the IPS network. The feasibility of the location area information is called coverage. The coverage includes from room to other indoor locations that can cover multiple rooms and indoor places.
- *Adaptiveness*: The system performance might be altered due to changes in the system. The adaptiveness to this technology is required since the advancement of multi-story buildings is coming day by day, and the need for IPS is rising high.
- *Cost*: The cost of the IPS system includes implementation costs, deployment costs and maintenance costs. Some installations are fixed installations, whereas some are dynamic, which improves the mobility of the system.

The Composition of the Indoor Positioning System (IPS) is presented below[6].

- *Dynamic the IPS platform of positioning of the system*: The mobility of placing the sensors across the network connected through the IPS provides a dynamic approach where the receptor is fixed and the sensor can be carried out throughout the network. i.e. the diagnosis sensors such as the camera, IR sensors, etc. which is movable and provides the real-time information to the IPS network, which makes the model a dynamic platform.

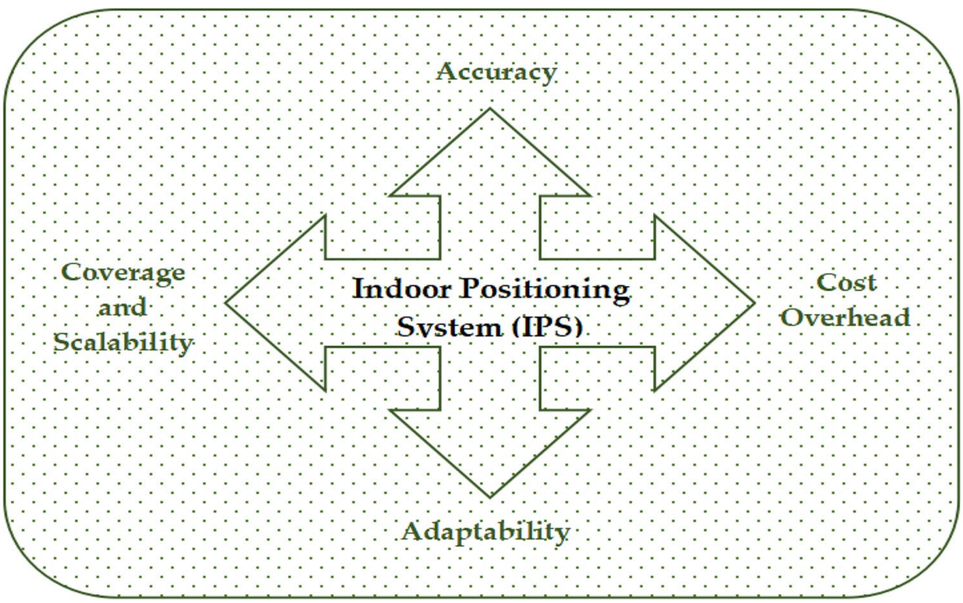

Figure 1. Vital features of IPS.

- *Location devices or signal transmitters*: The location devices as well the signal transmitters are the sensors and receptors used within the network of IPS. The signal transmitters here are called signal receptors which scan the signal received from the sensors and then further send for signal processing and data processing.
- *Signals retrieved by mobile phones to interpret signals*: The application which acts as a receptor for the signal and cam retrieve data and process through the application and analyze the data which shows the mobility of the application through Indoor Positioning of Devices and systems.

IPS is constructed as a network of devices used to provide a location to people or locate objects where Global Positioning system lack precision or fail, such as inside multi-story buildings, airports, alleys, parking garages, and locations where the GPS cannot reach or there is altitude changes not latitude or longitude changes. It uses a variety of devices such as WiFi and Bluetooth, camera, laser sensors, WiFi and the mobile device which can be placed indoors and the sensors and receptors would provide information based on the location. IPS can be considered as an adequate replacement of GPS technology where GPS technology cannot reach or cannot be used properly.

Growing demands in positioning systems have resulted in introducing positioning systems which will work indoors. The indoor based system will have its own set of services and use its application, sensors and devices. This technology can be implemented in the healthcare domain like in health diagnostic centers. IPS technologies are the systems which can be implemented indoors where the reach from one device to another is not possible. It can be connected by the variety of IoT devices which can be secured by the corresponding links. Here the state of art localization feature is used. The indoor positioning system is a boon for the hospitals where patients and the diagnosis teams can efficiently keep track of the patient's health status and diagnostic tests. The real-time indoor localization is Accurate, inexpensive, and reliable, which holds the capability of applications which are context-aware and IoT based location services. Hospitals, as well as healthcare units, play a vital role when it comes to the health of patients as treatment of patients at the right moment is the biggest deal. The patients have only been able to self-predict disease through emergency call or access Telephonic health support. In an emergency, both options may be difficult or impossible for the patient to access so that the emergency is quickly discovered by chance. The IPS system is a boon for the health care domain as it uses various sensors and receptors which takes the input and processes it. This technology works similar to GPS, where the location sensor is connected with a global positioning system. In contrast, here we have indoor positioning. All the sensors are connected to a sensor which is present indoors. And sensors information is processed, and reports are generated and send to the health care professional.

Skin cancer or melanoma is growing at its peak due to the penetration of UV rays into the body; either it can be growing in the pigmented cells or non-pigmented cells[7]. In the dangerous world of cancer, skin cancer is the most deadly as it comes into detection when it has already spread out; the malignant melanoma is one of the essential tumours. Since for at least 30 years, the rate of growth of melanoma has been rising, this is vital due to the high mortality, but among all the cancer cells the skin cancer occurs frequently. Dermoscopic images include specific geometrical properties that can be used to distinguish malignant and mild malignancies. Dermoscopic has been used to diagnose melanoma skin cancer rather than skin biopsy, which is a surgical procedure. This is a challenging task for several reasons. First, there was a substantial degree of intralayer variance between melanoma images, but little inter-layer variance among melanoma and non-melanoma images. Second, pictures of both malignant and benign tumors are very similar. Finally, hair-like sounds are always present in skin photographs, making them challenging to evaluate. In our suggested approach, we retrieved an innovative characteristic, namely the difference between the maximum and minimum Fret diameters of the ellipse most appropriate for the skin disease[8]. Melanoma classification is done using a variety of classic machine learning algorithms, including deep learning methods. However, more complex network structures do not achieve the model's efficiency enhancements. In this research, we attempt to increase the precision of CAD for melanoma by focusing on medically pertinent data. We present the Attention Zoom and Metadata Embedding (ZooME) melanoma identification network using:

1) introduced the Attention magnifying model for better extraction and use of unique pathological information from Dermoscopic images.
2) Integrate patient demographic details, such as age, gender, and anatomical location, to offer full data for accurate forecasting. We use a 10-fold cross-validation technique on the most recent ISIC-2020 dataset, which contains 33,126 Dermoscopic images[9]. The skin cancer or melanoma caused by ultraviolet rays due to relatively high sunlight exposure. Around 62000 new cases are detected every year in west countries[1011],. The classification of malignancies plays an important role in the diagnosis of skin lesions. However, the classification of malignancies is a difficult task, due to the variability in the shape of the skin lesions and interference from the dermoscopic images. In this research, we present the Multi-Level Skin Lesions Attention Learning Network (MASLL) for better melanoma categorization. Particularly, we create a local learning arm with a skin lesion locator (SLL) module to assist the neural network with acquiring the lesion features of the area of concern. Furthermore, we include a Weighted Feature Integration (WFI) module that combines both local and global branch lesion data, improving the capacity to differentiate skin lesion traits. The test results on the ISIC 2017 dataset show the effectiveness of the proposed method in classifying melanoma. Melanoma growth and development occurs except for the nodular type it occurs in two stages. The stage where the development is radial or horizontal near the epidermal stage is called "single cancer melanoma" is important in early detection. Melanoma can be spread metastatic, potentially Since the automatic detection of melanoma, there is a major challenge regarding the abnormal shape, size, location and color of the dermoscopy images. Furthermore, the treatment of melanoma seems to be a complicated task due to insufficient detail for diagnosis and limited visual examination. Therefore, an automated detection procedure is needed in dermoscopy

images to efficiently and rapidly detect and diagnose melanoma lesions. Therefore, we localized the melanoma using a single-stage object detection tool called Retina-net. The suggested framework is assessed using the PH2 dataset. Retina-net is a one-step object detection engine that quickly and precisely identifies melanoma. Additionally, focal loss was investigated to prevent a layer imbalance between normal skin pixels and the conspicuous melanoma segment. When employing PH2 sample images, the suggested system achieves an outstanding efficiency boost of up to 97%, resulting in average precision. Our method can be efficiently used to automate medical decision-support systems for easy melanoma diagnosis and prediction[12]. The melanoma has a recovery rate of more than 90%, but it must be detected at the earlier stage[13]. The Dermoscopy is the study of skin which allows understanding more about skin pigmentation and morphological structure which is done by detection of melanoma by the image samples collected from the patient by (ABCD) where A implies Asymmetric shape, B implies Border, C implies Colour and D suggests Diameter rule. The rule depends on medical experts as it is highly subjective[14]. Based on the sample collected from the patient, the report examination of subcutaneous is obtained according to the experience of medical professionals[15].

By the use of the IPS system, the disease detection becomes easy when sensing devices such as the camera, IR sensors, laser beams, UV detection as well as the electric cardiograph which takes input from the patient and disease detection becomes handy. The server processes the information, and the processor has predefined algorithms and module where the data is sent to process, and after processing, the proper diagnosis and detection of disease is obtained. This IPS technology can be effectively used to assist medical professionals in the disease diagnosis process, thereby helping them in treating and identifying cancer-like diseases. The IPS system can be used in healthcare domain for detection of conditions and its associated risk factors. Advanced computational devices and sensors can be used in clinical sites. The model shown in Fig. 2 presents a sample demonstration of disease diagnosis, which can be done through the sensors implemented at hospitals, and the result is obtained immediately.

The indoor positioning helps to keep a consistent track of the patient and can provide the health status parameters, as shown in the figure. The sensors are placed at the diagnosis room, which is interconnected and stores the captured image in the hospital database and can keep real-time track of the improvement in the patient's health. The samples are collected by the sensors in the diagnosis room and sent for the processing of the image as well as detection of disease risks. The indoor positioning system is loaded with camera and sensors which can capture a high-quality sample of the patient's affected region and can store into the database and fetch results immediately which can be reported directly to medical staffs and to family personnel of the patient. This will help to reduce the time of detection, and immediate treatment can be started. The patient is diagnosed automatically with effortless time, and the treatment is reduced as the patient is diagnosed, and reports are made at the same time, and the disease detection and evaluation occur at the same time.

This modern and advanced technology like IPS can be used in melanoma disease detection. The melanoma detection uses image capturing sensors which captures the images obtained from the patient's skin and then

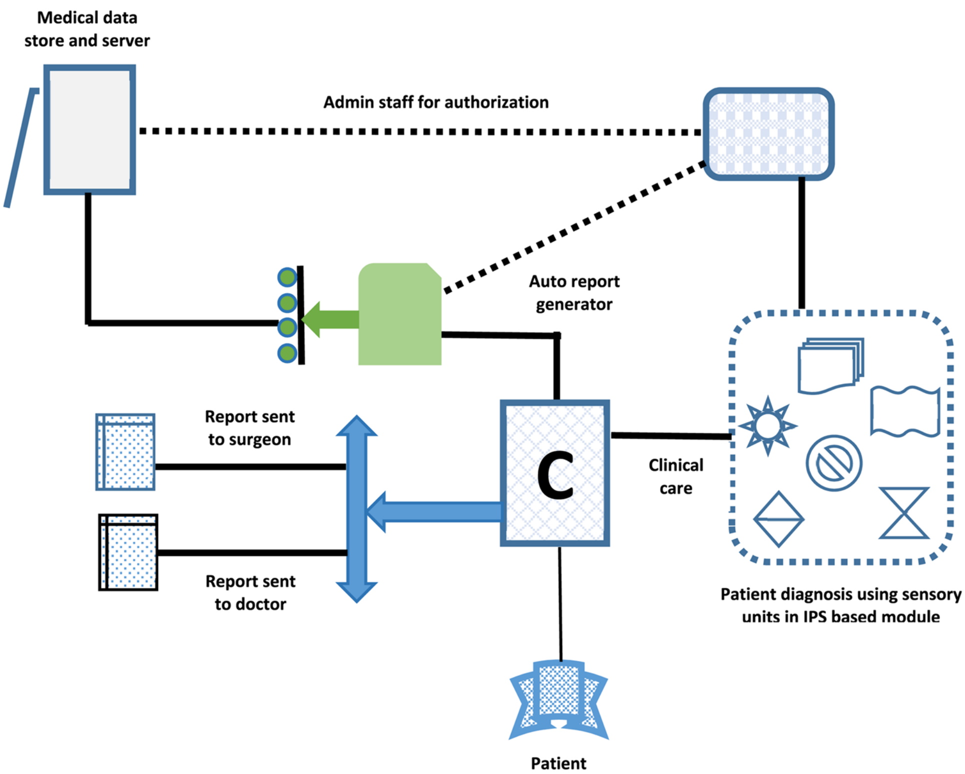

Figure 2. Depiction of an IPS based automated patient disease treatment in health care.

forwards it to processing. The model present at the processing end processes the images, and through various classification algorithms, it detects whether the patient has melanoma or not. For the detection of melanoma, advanced computational devices and sensors are used which are implemented at hospitals. The disease diagnosis is made through the sensors implemented at the hospitals, and the result is obtained immediately. The indoor positioning helps to keep a consistent track of the patient and can provide the stage of cancer. The sensors are interconnected and store the captured image in the hospital database and can keep real-time track of the improvement in the patient's health. The indoor positioning system is loaded with camera and sensors which can capture the high-quality sample of the patient's affected region and can store into the database and fetch results immediately and can report directly to the doctor or to the family personnel of the patient. This will help to reduce the time of detection, and immediate treatment could be started. Hence, the model is based on indoor positioning system can effectively utilize to detect melanoma using sensors and IoT devices can be successfully deployed in clinical centers. The model works remotely as it is based on IPC, and the model provided the mobility of the service.

The motive of research is to create an autonomous device for detection of melanoma that comprises of the multiple sensors to detect potential cancers and distinguish them into a normal mole or skin cancer as melanoma where the symptoms are not clear to patients. The set-up includes a faster prototype response and detection of cancer cells at an earlier stage. The device uses a Raspbian operating system which is fast and compact in its segment, and it generates a response either to the system or the device used as a monitor. The feature selection of the input values obtained from various sensors is carried out. This process is a two way the cumulative feature selection, which used input from two distinct sensors and is responsible for getting the responses which are used to merge and determine the equivalent features. On top of its classification of images are performed using Fused-KNN, which results in higher classification accuracy.

The main contributions of this paper are as follows:

- A succinct assessment of Indoor Positioning System using routers and sensors are explored in this study.
- This research presents a novel smart and intelligent indoor positioning model for melanoma disease detection using image samples. The model involves a hybrid integration of data aggregation using sensors, data optimization, feature extraction and classification using Fused-KNN approach.
- The model generated encouraging results upon implementation in context to evaluated metrics like accuracy, error rate, latency and others among them.
- Thus the proposed hybrid IPS based remote model can be effective in not only predicting melanoma risks in patients but also similar disease disorders in a robust manner.

The paper segmented as follows. Section II explains about the literature review conducted for fetching out various technologies, till date and also discussed different methods which have been opted by various researchers for the detection of melanoma using multiple techniques and the strategies. Section III has proposed a model which involves the complete methodology for the detection of the melanoma. Section IV focused on the statistics of human beings to the melanoma as well as the result obtained while performing the model analysis. Section V consists of the conclusion and future scope of the paper.

Literature survey

The detection of skin diseases by image processing is a vital topic for image processing as well as computational processing using sensors, actuators and data perception. Extensive research is being carried out in this domain using different machine learning techniques and using various sensors and other modern devices. The research on medical symptoms of the skin includes of skin disease analysis and chemical analysis of skin markers. In[16]they proposed the study of various cells such as inflammatory dendritic epidermal cells, plasmacytoid dendritic cells and Langerhans cells how act upon the influence of defence against anti-viral skin infection. In[17]used a gold standard diagnostic tool for detecting skin diseases and also discussed, which is the anti-bodies analysis and mucous membranes. The usage of this method includes immunology fluorescence microscopy and well as usage of various commercialized tools. They also included that influence of antigens in skin characterization for diagnosis of serological. One kind of skin cancer called melanoma begins in the melanocytes, which are the cells that determine your skin tone. It is the deadliest skin disease, accounting for 77 fatalities. To lower these fatalities and enable more straightforward surgeries and treatments, early detection is essential. Our recommendation is to use sophisticated deep neural networks to identify melanoma automatically. Due to doctors' hectic schedules, there aren't enough annotated photos for these deep-learning models to function well. Utilizing fewer data points, the suggested methodology teaches an opponent how to attain greater accuracy. This enhances the picture's depth and gradient by considering dimension and shadows by eliminating extraneous details and noises. Using this technique, a new adversarial picture enhances the input's loss and is produced using the gradient of the input image's loss. Testing and training are both employed using synthetic visuals. On the VGG16, VGG19, Densenet121, and ResNet101 models, a comparison analysis of adversarial and non-adversarial training is given. The best classification accuracy for melanoma was 84.77%, attained by ResNet101 using adversarial training. Classifying benign and malignant tumors is done well with this strategy. The author[18]presented a transcription profiling-based approach for the identification of psoriasis, atopic dermatitis, and contact dermatitis. Using their degree of judgment, the protein expression levels were used to diagnose the illness. In[19]the authors had developed a model for detection of melanoma. Authors developed a system which includes proposed skin lesions ensemble method with deep learning. The most deadly kind of skin cancer is melanoma. To enhance melanoma detection, automated diagnostic tools have been created.Different forms of lesions can be distinguished from one another by their varying boundaries in the skin. In this paper, an accurate contour descriptor for concave contours is introduced. It acquires boundary intersection-based signatures (BIBS) Fourier and wavelet descriptors. Support vector machines are employed in classification. Compared to conventional contour signatures, BIBS performs better. In dermatology information systems using the DermQuest dataset, combining BIBS Fourier descriptors with other features produced the best results with an accuracy of 91.72%, sensitivity of 92.02%, specificity of 88.08%, and correctness of 90.34%. Their approach to detect skin lesion and detection of melanoma is expressed in[20]. The techniques for identifying melanoma and skin lesions are explained in[20]. Melanocytes, the cells that create pigments on the skin, are targeted by melanoma, a kind of skin cancer. This inquiry focuses on two types of melanoma: nodular melanoma and lentigo melanoma. Maligna Lentigo Solar lentigines are used to identify melanoma, while melanocytes nevus is used to identify nodular melanoma. This debate centers on the Variable Centered Intelligent Rule System (VCIRS). To maximize the benefits of Variable Usage Rate (VUR), Node Usage Rate (NUR), and Rule Usage Rate, VCIRS combines a rule-based system (RBS) with Ripple Down Rules (RDR). Users can give the symptoms they are experiencing with this novel approach, which is based on the operating system Android. The system then uses this information to figure out whether the user suffers from the condition. They proposed the identification of melanoma utilizing segmentation and extraction of features depending on the center of the melanoma, where they extracted part of Lesion Indexing Network that uses CRN as the main detection method. In[21]In men, Skin cancer is an extremely prevalent and deadly form of cancer. Melanoma is a fatal kind of skin cancer. If identified early, it is easily treated. Melanoma is diagnosed with a biopsy, which can be traumatic and complicated. This paper describes a computer-aided detection technique to facilitate early melanoma diagnosis. An effective diagnostic system is created by combining image processing techniques and support vector machine (SVM) methods. Pictures of the damaged skin are collected and analyzed using various approaches to produce enhanced and normalized pictures. The photos are segmented using morphology and thresholding approaches. The skin image's fundamental characteristics such as texture, color, and shape are obtained. The Grayscale Co-occurrence Matrix Method (GLCM) is used to extract textural information. The retrieved GLCM, color, and form features feed into the SVM classifier. It classifies the picture as malignant or benign melanoma. When combined with GLCM forms, colors, and features, the classification algorithm obtains an accuracy of 83%. While in[22]the authors made an illustrative comparison of mobile applications for detection of melanoma and another skin disease. The authors evaluated various apps and explored their capacity for effective and extensible image processing with smartphone cameras and sensor technology. They also discussed the legal implications of creating medical applications that are moral, high-quality, and accessible. Baldrick et al. received 95% using the sensitivity using a computer application and 88% as specificity, also even they calculated the sensitivity of dermatology as 91.67% and 91.43% as specificity[23]. Mortaz et al. made a research analysis and founded an artificial neural network (ANN) as well as Genetic Algorithm technique for detection of melanoma with 91.67% as sensitivity and 91.43% as specificity[24]. The author Kamasak et al. Found methods to classify the image samples collected from the patient by extraction of identifiers using Fourier and also the legion part after splitting the samples and received an accuracy of 83.33%[25]. Author Fidan et al. made a research on the exact classification of melanoma which has come out to be 93.33% in which the extraction of data using PH2 data set applying ANN used for detection of abnormal melanoma[26]. Author Baştürk et al. Introduced a method for detection of melanoma which is called Deep Neural Network (DNN) using DNN they received an accuracy of 91.85%[27]Using IoT devices in healthcare domains the detection of disease has been made easy and reliable where a variety of classifications can be employed to monitor human factors[28]. McGrath and Scanaill[29]outline the numerous wearable sensors utilized for individual wellness mobility in excellent detail. Several wearable devices with sensors have become accessible on the marketplace, with heart rate, pulse, blood pressure, body temperature, breathing rate, and levels of blood glucose used as variables[30]. Another intriguing IoT device is skin monitoring patches, which can be applied on the body resembling tattoos. Patches can be applied and deregulated at a cheap price. The individual can utilize those for many years to monitor a vital health factor[31]. Melanoma is a highly serious illness, and the occurrence of skin malignancies is increasing. Potential indicators of melanoma development include tumor cell proliferation rate and lymphatic and vascular density. This study intended to compare tumor proliferation and vasculature development in original tumors with early blood and lymphatic metastasis. The detection of IHC was conducted on paraffin-embedded pieces according to the standard method. Direct monoclonal antibodies against lymphatic endothelial podoplanin (MONOSAN), against blood endothelial CD34 (NOVOCASTRA), proliferation marker Ki67 (NOVOCCASTRA), and tumor marker S100 (ABCAM) were used. Tumor growth activity and tumor vessel volume have been found to grow in the main tumor during early plasma metastases. It has been observed that tumor growth and tumor lymph vascular volume densities are elevated in the initial tumor during early lymph metastases. These findings suggest that the proliferation of tumor cells percentage, as well as lymphatic and vascular volume, may be associated with skin melanoma development and serve as predictive indicators for hematological metastasis and early lymphatic system. The electrical elements are embedded in the rubbery construction and can communicate sensor data via a wireless medium. Human health conditions can be transmitted to doctors in real-time via sophisticated and smart IoT gadgets[32,33]. Almotiri et al.[34] suggest a mobile healthcare approach that uses wearable gadgets and a cellular network of sensors to gather human information in real-time. The information has been preserved on the internet and provided accessible for the diagnosis of patients. Access is limited to a specific authorized group. An intelligent ICU system was created by Chiuchisan et al.[35] to alert and instruct physicians and relatives when their patients' vital signs and gait become erratic. If necessary, changes in the surrounding environment are also significant indicators that action has to be taken. Shuchi et al.[36]assess the outcomes of various algorithms based on machine learning applied to a range of skin conditions[37]. employs the mobile dermoscopic device to acquire photos and transmit them to the server for computer processing. In[38], The mobile system working feature presented a preliminary system for legion detection using a basic threshold method only standard colour and feature is considered for the legion selection. Recently, the works[39] proposed a model which segment and extract legions along with visual features. The texture features and automated colors, with added human-annotated based information, which include locations

Work	Preprocessing	Classifier	Accuracy rate
1	Gray level Thresholding	SVM	90%
2	Sequential Dermoscopic Images	ANN	61.88%
3	Re-sizing, Cropping, Hair Removal	CNN	91.73%
4	Histogram Quantization	Thresholds Discriminate	60%
9	lesion borders were obtained manually	RBF	92.81%
12	Blure filter	Neuro-fuzzy	95.24%%
13	Re-sizing and Color space Transformation	MLP	97%
17	Image contour Tracing Algorithm	Clustering	84.77%
18	Watershed method	Fuzzy System	91.72%
20	Median Filter	FP-ANN	80.51%
21	Median filter	NB	83%
31	Image resizes	PSVM	93%

Table 1. Relevant research on melanoma disease diagnosis using computational methods.

Existing work	Methodology used	Results obtained
40	Multiple trained deep learning models like CNN and ResNet 50 were applied to extract attributes and stacking technique using various models were utilized to classify skin cancer scans	Accuracy = 90.9%
41	As many as 11 deep neural networks were validated on skin cancer data to design a mobile healthcare framework and Densenet gave best outcome.	Accuracy = 92.25%
42	13 transfer learning based algorithms were validated to categorize skin cancer image data where Densenet201 gave best result.	Accuracy = 82.9%
43	Multiple phases based hybridized cognitive model on VGG were deployed with three dimensional wavelets.	Accuracy = 93.33%
44	A novel integrated parameter transfer driven segmentation based classifier was presented to classify skin cancer dataset.	Accuracy = 91.03%
45	7 distinct deep cognitive models like DenseNet201, MobileNet were used for skin cancer categorization problem.	Accuracy = 76.09%
46	Various predictive analytics approaches like CNN and VGG-16 were evaluated to categorize skin cancer risks.	Accuracy = 88%
47	Applied Used advanced neural networks which involved time in its working principle to classify skin cancer data.	Accuracy = 89.57%
48	Proposed a hybridized deep neural network framework to classify skin cancer image set using models like ResNet152V2, MobileNetV2 and DenseNet.	Accuracy = 89%

Table 2. Analysis of deep learning models on melanoma detection.

of the legion, number of lesions, lesion size so on, are also used to distinguish melanoma from others. Table 1 highlights some vital research works undertaken in melanoma diagnosis using computational techniques.

Identified research gaps for the study are as follows:

- Counters image crop and RGB to Color detection is not explored much as in such cases low probability image can be extended using Data Augmentation.
- CNN and SVM classifiers are used with less feature injection methods in the vascular and Lymph.
- ANN Classifier is used and during feature extraction the external parameters are not considered.
- Mobility of optimizing the interface and introducing the wide aspect to receive the data using sensors and their adaptability to the process of image extraction is not yet covered.
- Red Scaled image consisting of Skin color range and temperature using the variable sensor type to detect the gaps in feature extraction is not yet explored and not covered.

Based on recent studies, some models used latest deep learning models like DenseNet, Mobile-net and VGG-19 algorithms among others. Table 2 summarizes some latest works, their methodology used and outcome obtained on melanoma analysis using deep learning models.

Materials and methods

This section presents the computational techniques used in the task of melanoma disease diagnosis. Hardware and software requirements and system configuration is also highlighted. Dataset used in the research analysis is also discussed in this section.

The dataset used for the evaluation of the work is SIIM-ISIC Dataset 2020 having 33,126 DICOM images with embedded metadata[49]. Here the images in the dataset are present is Digital Imaging and Communications in Medicine (DICOM) format which is easily accessible by the pydicom, containing images and metadata which is commonly used in imaging data format. The images in the dataset are provided in JPEG as well as TF record. The TF record of the image has been resized to 1024 *1024. The CSV files in the dataset contain the metadata. The dataset contains the field of JPEG which consists of the Digital Imaging and Communications in Medicine (DICOM) images, train dataset, tf-records, train.csv and test.csv files. A total of 11,000 images are present in the dataset. Details of metadata are summarized in Table 3.

Attributes	Details
Image_name	File name as unique identifier referencing to
Patient_id	The identifier of unique patient id
Sex	The gender of the patient
Age_approx	The approx. age of the patient
Anatom_site_general_challenge	The data of location of image site
Diagnosis	Diagnosis detailed information
Benign_ malignant	Te indicator to the malignancy of imaged legion
Target-binarized	The binary version of target value

Table 3. Melanoma dataset details.

Tools used	Specification	System Requirements
Hardware	Processor	Arduino Atmega 328- *P* Controller
	System Processor	AMD
	RAM	8GB
	WiFi - Arduino	WIFI LSP 8266 Module
	Monitor	HP Monitor
	CAM Sensor 1	CCD
	CAM Sensor 2	CMOS
	LASER Sensor 1	IR Sensor
	LASER Sensor 2	LIDAR
Software	Operating system	WINDOWS
	Database used	POST GRE SQL
	Language	PYTHON IDE
	Data Visualization	JUPYTER Notebook
	Model Training and Validation	PYCHARM
	Database	MYSQL DB
	Deployment Model	HERUKU

Table 4. System configuration used for the study.

Different configuration requirements are deployed in the model in the analysis. Tools for analysis, processing, development and visualization are utilized for the purpose. The overall system configuration, which includes hardware, as well as software requirements for the model, is shown in below Table 4.

The sensors used in our model include:

- CMOS Complementary Metal Oxide Semiconductor.
- CCD Charge Coupled Device.
- IR Infrared Sensors.
- LIDAR Light Detection and Ranging.

When a patient enters into the diagnosis room, we have placed 4 sensors in which we have 2 sensors for Camera and 2 sensors for laser imaging, The reason behind using the laser sampling camera sampling images can capture only colour and area of visibility of the melanoma spot but through laser sampling we are able to get the structure and surface area and shape of the melanoma which is present over the skin. The sensors CMOS is used to capture the image pixels one by one which will help in getting exact colour of the sample which is captured in sequential order where as CCD captures the light at the same time here and focus on the sample area at a time, The CCD has a advantage of getting magnified image and non - Skewed image where as CMOS has advantage of getting clear colourful image. IR and LIDAR both produce graphical 3D image which detect shape and structure of the sample. IR sensor has the capability to capture image at low light condition and can produce a camouflage image highlighting the affected region in the sample where as the LIDAR can capture The structure and surface occupied by melanoma/mole in the sample.

As discussed above, the IPS based melanoma detection model presented in this study uses routers and sensors as illustrated in Fig. 3. The distance of objects between the routers determine the location of the patient indoors. This system helps in localization of sensors based on the location of the patient. The location of the patient is calculated from the routers and through this and hence it determines the location of the patient inside the diagnosis room and the data is collected by the sensors and sent to the routers which further forwards to the next server for processing of the image sample. Here the sensors used are IR and LIDAR for laser sampling and

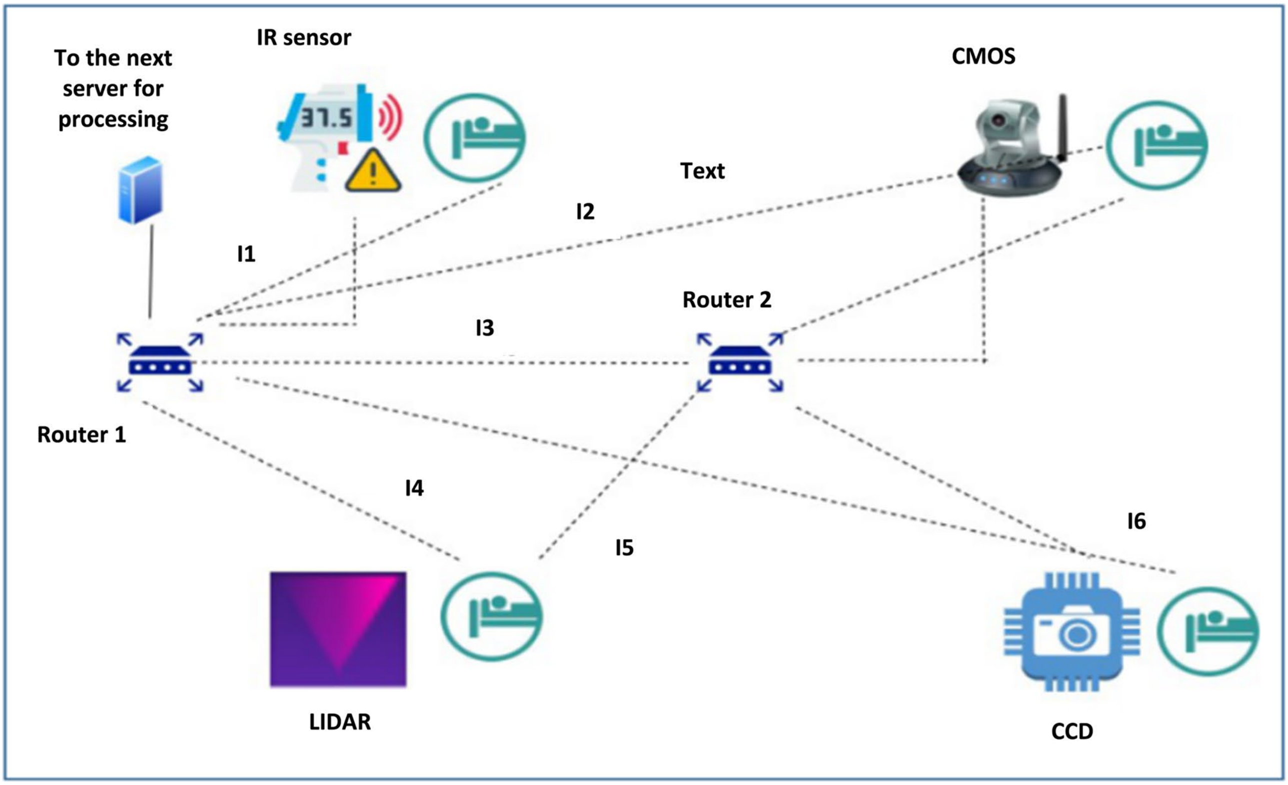

Figure 3. IPS based model using routers and sensors.

CCD and CMOS for camera image sampling. The router inside the diagnosis room depicts the location of the patient and tells which sample is collected real time.

Different computational techniques find their utilization in this research study. These techniques are discussed in this section.

- *Image Detection*: In this process the pictured captured using the camera consisting of the sensors CCD and CMOS is scaled based on the field area, cropped based on the density and optimized based on the picture angle. The image scaling is an important feature in this process as it is responsible for the proper format and size of images.
- *Hair Removal*: The skin consists of hairs which should be removed by the intelligent process of image extraction, so here we use Morphology method to remove the hair, and we obtain the accurate picture of the sample.
- *Image Restoration*: The image obtained using the laser sensor by IR sensor and LIDAR, which is polychromatic consists of hue and noise, therefore to reduce the noise, we stabilize the hue and RGB balancing. This process is important to ensure the shape and structure of the sample is clearly visible.
- *Normalized Cross-correlation*: The process of finding out the similarity between images. Through this algorithm, the image is allowed to compare. We compare the image from the camera as well as the image from the laser. If the value of the similarity is close to 1, we can say the image is similar else not similar.
- *Image Segmentation*: In this process, the images obtained from both the sensors is collected and overlapped to get a structured image which is far accurate than the existing image as it has colour and structure accuracy.
- *Coarse Localization*: The texture and structure of the skin and the area of the sample is optimized after image segmentation so the skin and the area of judgement can be well differentiated.

The proposed intelligent IPS based Melanoma detection model consists of a processing system which includes sensors like a vision sensor, which has a high definition camera to capture images from the user to take multiple shots. It consists of a laser beam which transmits light to the skin and detects the RBC and gets an image for the reflected beam of light which is denoted as the dropper laser light when it detects the RBC. Then both images of the same sample are used for detection, and it is taken as the total into consideration, and hence the prototype model developed will return better accuracy. In this model, we are using raspberry pie three and the camera is HD cam. The laser beam emitted from the sensors will be collected back, and the image obtained is generalized for consideration. The initial image is the image from the camera and the second image is the image produced after receiving the light emission of the reflection from the laser. The laser beam has a good result and scope as it can penetrate into the skin and generate an image based on reflection from the surface. Like if there is an RBC, it will detect as RBC, and if an image of melanoma is presented, then it will generate an image of the melanoma. The proposed framework diagram is explained in the below Fig. 4.

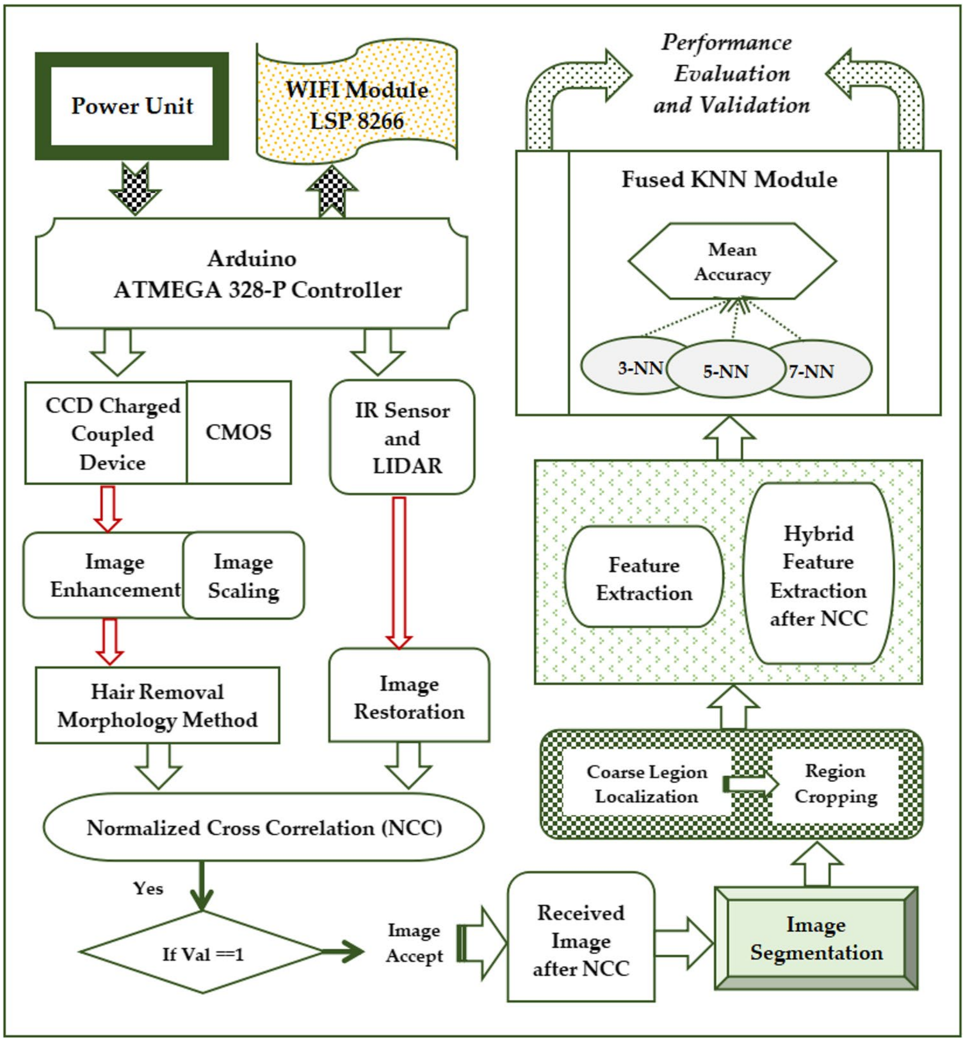

Figure 4. Proposed intelligent IPS based melanoma detection model using fused-KNN.

The device is powered by a powered unit, which is used by the ARDUINO ATMEGA-328 P Controller. The ARDUINO has the processing capability by using data from various sensors. The device consists of the following sensors:

- CCD - Charged coupled device sensor used along with the device to capture the outer layer of the segment of the melanoma at several angular clicks.
- CMOS - Complementary metal-oxide-semiconductor is an IoT sensing device which enhances the imaging quality of the pictures taken.
- IR SENSOR- Infrared sensor is a laser imaging technology used in our project to obtain a high precision image of the shape of the picture captured of the sample.
- LIDAR - LIDAR sensor is accompanied by the IR sensor which provides Better imaging of the shape of the sample to be taken.
- WIFI MODULE LSP 8266 - The WIFI module is attached to process the sampling and classifying the sample and carry forward the result obtained to either to Doctor or health care professionals.

The image sample obtained from the sensors is then processed, and images obtained from the camera sensors such as CCD and CMOS are further taken for image enhancement where image scaling is done such as cropping, shaping and adjusting the hue. After the image enhancement, the hair removal for the sampling is done through the morphology method. The image is finally kept for comparison with the image obtained through laser imaging. The image sample of the laser sample is collected using the IR sensors where it captures the shape of the sample and the LIDAR sensor to get the overall structure of the sample. The image obtained using the sensor is in the form of B/W. So at this stage, the image contains noise; thus, an image restoration method is used to remove the noise from the image. The resultant image is kept for comparison. The Normalized Cross Correlation is a process of comparison of two images. The output through the method is considered as the image accuracy is closer to 1. If the value of the comparison is closer to 1, then the images are similar or else, it is discarded.

Hence the image is overlapped through the Normalized Cross Correlation, and then the image segmentation of both the images are done where they both overlapped images give better visibility and shape and structure of the image is clearly visible along with the colour of the sample. The coarse legion localization is used for getting the texture of the sample, which are ups, downs and volume of the spread of the texture. The skin and the mole or melanoma texture is differentiated accordingly here. The region cropping was done to ensure the proper segmentation of the sample. The sample is then forwarded to the feature selection process.

The feature extraction process broadly involves the detection of melanoma using the two-way feature extraction, i.e. one using the camera and the other using the laser imaging. Both the features are extracted, and the same features are extracted from both the images. The human body is mostly wrapped in hair, which comes in a variety of texture and hues. Other artifacts might also be seen in skin photos. To eliminate these sounds from the supplied picture, pre-processing is done. This article describes how to eliminate black hair from a picture using the Dull-Razor algorithm. Adaptive median filtering, bilinear interpolation, and grayscale morphological closure are all components of the Dull-Razor method. In the preprocessing phase, an average filtering with a window dimension of 25 is utilized after the Dull algorithm - Razor to eliminate tiny hairs and other noises like air particles and noises produced during picture collection with the cameras, etc. In the following stage of subdivision, this additionally eliminates the subdivided picture's outlines. The subdivided picture's outline will appear jagged, zigzag, and have sharp edges when the size of the window is too tiny, making it practically hard to evaluate and obtain features in the following phase while scaling. Images with extremely smooth borders and shadows are typically associated with bigger window dimensions. lose its crucial information. For the segmented image to be effectively examined, the window size must therefore be neither excessively big nor too tiny. Due to the high-grade variation in the melanoma picture and the low-grade distinction between melanoma and benign tumors, delineation is one of its most challenging steps. This work employs a two-stage segmentation algorithm: the first phase uses Otsu's threshold approach, and the final segmentation uses Chan and Vese's approach. The picture in grayscale is transformed into a globally defined binary picture using Otsu's approach. This algorithm finds the perfect threshold for separating two categories that vary to ensure they have a minimum or comparable variation between classes and a maximum between categories. It operates under the assumption that the picture contains a pair of pixels based on the bidirectional histogram (the forefront of the pixels that participate in the object of the image that is relevant and expert pixels). To distinguish the item from the backdrop, an automatic grayscale threshold value is first determined using the object's grayscale distribution. At this threshold value, the variation between classes is then computed. The ideal threshold for dividing the image into objects and backgrounds is determined by taking the value that corresponds to the largest variation between the layers.

Figure 5 shows the laser is used for transmitting the laser beam into the skin and generation of the result is obtained by the reflection of the laser beam after getting an obstacle as shown in the figure. If melanoma, it will detect the melanoma cells under the skin and give us a b/w image of the melanoma cells. The melanoma cells b/w is matched with the RGB pixels of the colour images. The features are matched and extracted.

As shown, the RGB pixels are considered first with single colour images and the percentage of accuracy, sensitivity and specificity are obtained. The similar process is done with the colors of Red, Green and Blue. After the single pixel's accuracy percentage, the combined analysis of the (R + G + B) is taken for consideration, and the

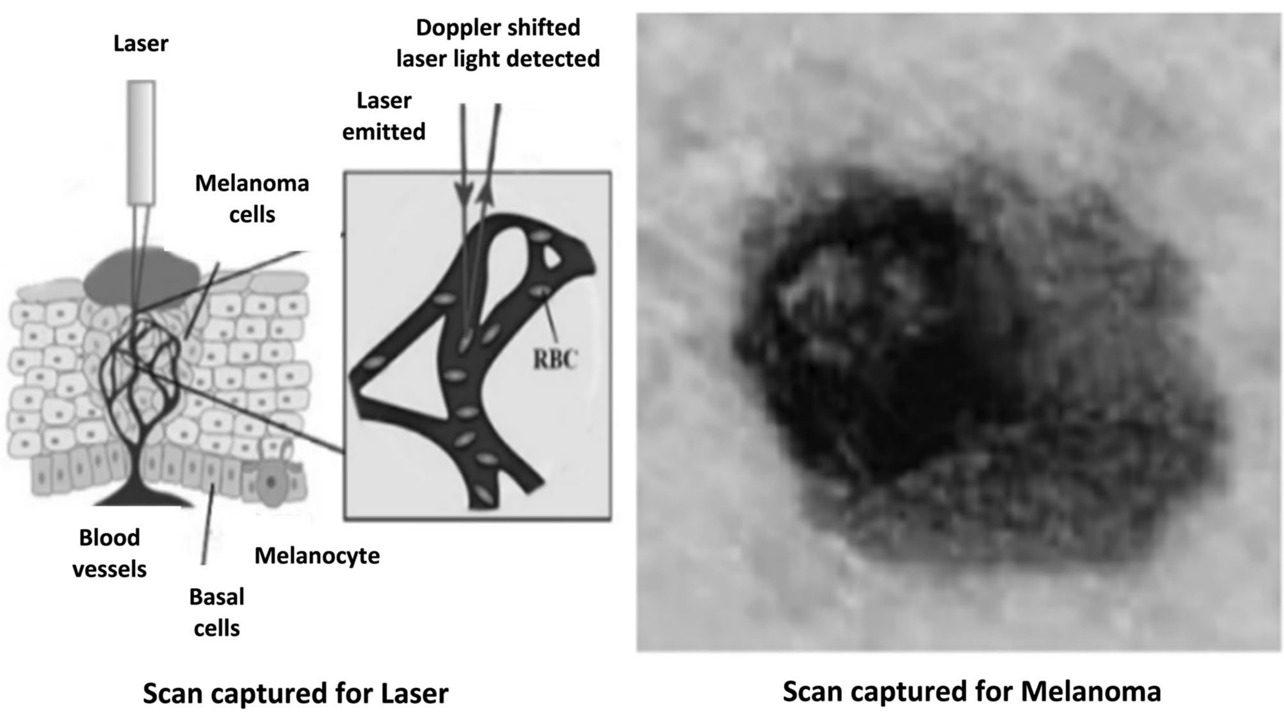

Figure 5. Feature extraction process.

optimum accuracy is fetched. This result will fetch the combined analysis, and then the prediction is made if the cancer cell or the image from the cancer cell is benign or melanoma on the top of the feature extraction several classifiers are tested for getting the better accuracy. Figure 6 shows the RGB image after the feature extraction of the Benign and melanoma cells. The image went through exploratory data analysis, and then the images are used for the feature extraction process. Both the images are obtained from the ISIC datasets, and the feature extraction processes are made. The feature selection process considered here consists of normal feature selection as well as the hybrid feature selection. Where in normal feature selection process only the (R G B) is extracted, and in the process of hybrid feature selection, the texture, shape and structure of the sample is considered. After the feature extraction, the sample is carried forward for classifier fusion.

The image obtained from the laser is as below which gets into the skin and reflects back the laser beams after detecting the RBC and the picture will depict whether it is RBC or melanoma hence the confusion between the mole or the melanoma will be eradicated. Figure 7 shown in the pictures obtained using the penetration of laser beam imaging. The B/W image is obtained from laser sampling, which is shown below in the figure.

The output of feature extraction is fed into the Fused-KNN module. Fused-KNN act as the aggregated classification module, which generates the aggregated classification accuracy and further predicts the class label of the testing image sample fed into the module. K-nearest neighbor algorithm is a simple and instance-based learner which usually offers very impressive performance. Prime benefits of using KNN algorithm is due to its simple and robust implementation with respect to search space. Also, it incurs less operational overhead. Here three distinct variants of KNN algorithm is employed, which include 3-NN, 5-NN and 7-NN.

The operational procedure of KNN is initialized in a parallel manner with the three considered values of K. For every data sample in the testing set, euclidean distance is determined for all training samples. The computed euclidean distance list is gathered, stored and sorted in ascending order sequence. Among the list, first k data points are chosen. The major class label is selected from the obtained data sample points, and the class label is provided accordingly. The identical procedure is followed to generate the class label for all three nearest neighbour algorithms in a parallel fashion. Voting is performed on the class label generated. Thus the class label with highest vote count is finally assigned the resultant predicted class. Simultaneously the classification accuracy rate is generated for all three classifiers (3-NN, 5-NN and 7-NN). A simple average mean of the accuracy is computed to get the aggregated classification accuracy. This generated accuracy is labeled as the accuracy for Fused-KNN. Figure 8 depicts the overall pseudo-code of Fused-KNN algorithm used in the research analysis.

After predicting the final class label, the performance evaluation of the proposed model is undertaken using appropriate performance indicators. From the dataset SIIM-ISIC Melanoma Classification which is used to train and test the model, the fivefold cross-validation system is used. The performance measures are calculated by using the parameters such as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) obtained from the confusion matrix. The classification criteria are stated as:

- The number of cases detected as melanoma: TP.
- The number of instances incorrectly detected as melanoma: FP.

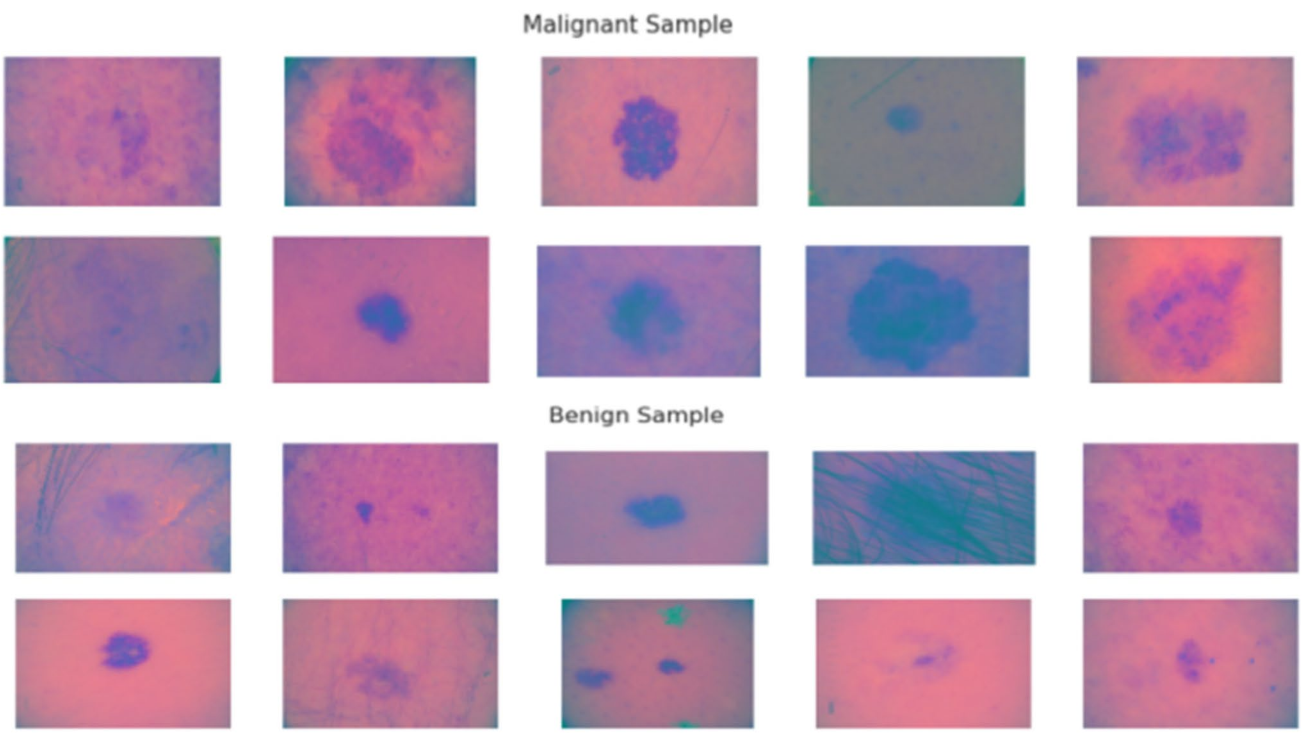

Figure 6. Malignant and benign melanoma sample obtained from ISIC dataset (R + G + B).

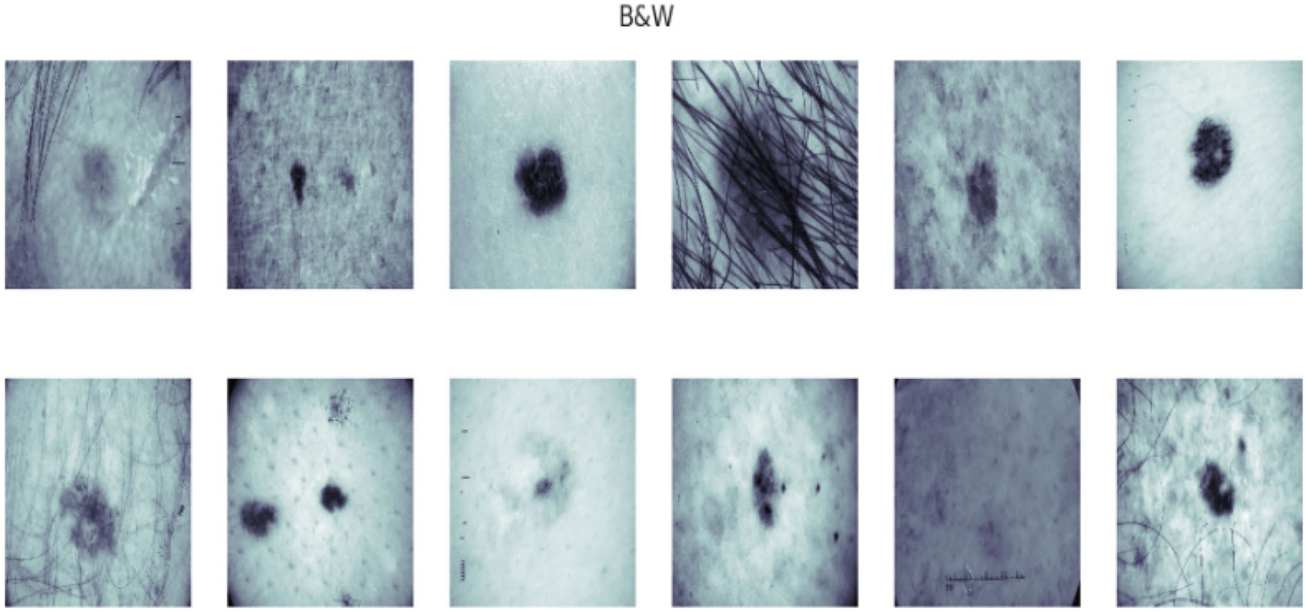

Figure 7. B/W image obtained by laser sampling ISIC dataset.

1. Aggregate training image and testing image samples.
2. Feed into Fused KNN module.
3. Parallel Initialization of Nearest Neighbour procedure with varying K.
4. Value of K chosen as 3, 5 and 7 in parallel.
5. For every data point in test sample:
   5.1. Determine Euclidean distance to all training sample points.
   5.2. Euclidean distance list stored and sorted in ascending order.
   5.3. First k points selected.
   5.4. Identify major class label from selected sample points.
   5.5. Class label allotted to testing sample.
6. Gather class label from all 3 nearest neighbour classifier in parallel.
7. Simple voting procedure applied on predicted class label obtained.
8. Predicted class with maximum votes declared the aggregated output class.
9. Aggregated output class assigned as the final predicted class label for test data.
10. Compute accuracy from all nearest neighbours in parallel.
11. Find average mean of all accuracy obtained.
12. Aggregated accuracy is the resulting accuracy retrieved for Fused KNN.
13. End

Figure 8. Pseudo code for fused-KNN algorithm.

- The number of patients correctly seen as non-melanoma: TN.
- The number of cases incorrectly detected as melanoma: FN.

Various performance metrics used in the studies are discussed here.

Accuracy: The ability of the system which can differentiate the melanoma and nevus cases correctly.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

Precision: It is the fraction of relevant instances among the retrieved samples.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

Recall: It is the fraction of the total amount of relevant instances that were actually retrieved.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

F-Score: F-score is a measure of a test's accuracy in terms of the harmonic mean of precision and recall.

$$\text{F} - \text{Score} = \frac{\text{TP}}{\text{TP} + 1/2\,(\text{FP} + \text{FN})} \tag{4}$$

RMSE: It is the standard deviation of the residuals, which is the mean of expected values and observed values.

$$RMSE = \sqrt{\overline{(F{-}O^2)}} \tag{5}$$

f = forecasts (expected values)

o = observed values (known results)

MAE: The average absolute vertical or horizontal distance between each point in a scatter plot and the Y = X line.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{\text{n}} \tag{6}$$

MAE = mean absolute error

y_i= prediction

x_i = true value

n = total number of data points

The overall data flow structure is illustrated in Fig. 9. As highlighted, the components of the IPS unit is the initial module of the prototype. Input source equipped by different sensors is regulated by the IPS unit consisting of various signaling sources. It is followed by data collection through sensors and laser scans from patients. The collected samples are analyzed through image processing where sampling and restoration of images occurs along with noise reduction. Similarities between the analyzed camera images and laser samples are identified using the NCC algorithm and further overlapping images are validated. The relevant features are then retrieved and the IPS driven Fused-KNN model is deployed for melanoma detection. The results are evaluated with various vital metrics like accuracy, precision and error rate among others.

Implementations and results

The melanoma dataset is divided into 80% training and 20% testing data using a 10-fold cross-validation method. This method splits the data into 10 sub-parts where 9 of those are assigned for training and 1 part is used for testing. The procedure repeats for 10 times and each round uses a distinct fold as the testing set. The outcome from every split is computed to obtain the mean value. Reason for splitting the data into 80:20 ratio is because the model recorded best accuracy with this division.

To validate this research work statistical analysis is crucial. The statistical tools and software used for the analysis are mentioned as follows.

- Python programming language is used to implement the Fused-KNN model with (3-NN, 5-NN, and 7-NN)
- Scikit Learn Library is used for utilizing the predictive algorithms including the KNN algorithm to calculate the precision, recall, F1 score, and accuracy.
- NumPy and Pandas Library are applied for data analysis, feature extraction, and selection.
- Anaconda Navigator, Jupyter Notebook and Pycharm provided the software framework.
- MySQL database is used for data storage and processing.

The dataset is divided into sample sets done using jupyter notebook. The sample is classified and visualized on the basis of the Dataset ISIC SIIM. The Fused-KNN consists of the fusion of 3NN, 5NN and 7NN with their mean accuracy, which results in more accuracy than the existing classifiers. The KNN model uses a standardized geometry method to determine the input type and that is the reason for selecting KNN Classifier as the most

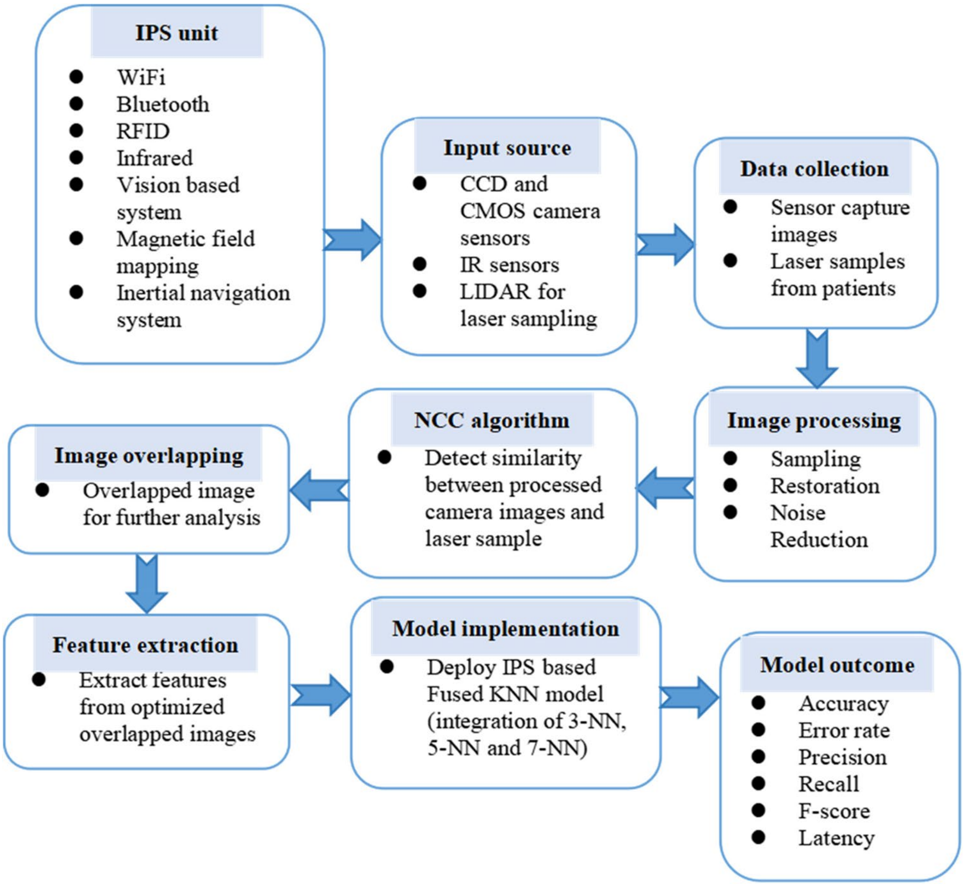

Figure 9. Data flow prototype of the proposed model.

favorable Classifier in our research. The application of the k-nearest-neighbors method has the following advantages:

- It is straightforward to apply and comprehend; and because it makes no assumptions about the underlying data,
- It is perfect for nonlinear data.
- Multi-class cases are automatically handled by it.
- With adequate representative data, it can function successfully.

Figure 10 depicts the comparison analysis of various classifiers applied on the melanoma image dataset, where Naive Bayes is yielding a significantly less accuracy of only 55% while C4.5 is generating a good 96.71% accuracy rate. The proposed IPS based Fused-KNN model outperformed all other classifiers giving a maximum accuracy of 97.8%. The Fused-KNN here uses three folds, using the results using the fusion of these three classifiers, we have achieved the highest accuracy other than the classifiers. The folds in the KNN as well as being dependent on the IPS, which uses multiple receptors, has increased the accuracy of the model.

Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are the two precise metrics used to determine the misclassification rate with respect to error rate as it gives an estimation between the predicted and the actual value obtained after classification. As seen in Fig. 11, SVM gave a very high MAE value with 1.564 while classification along with decision tree gave a good performance with only 0.3785 rates of error. As far as RMSE is concerned, again SVM produced poorly with 2.212 and decision tree produced relatively less RMSE value with only 0.894. The performance of the proposed IPS base Fused-KNN model was proved to be very optimal when compared with other classifiers. MAE and RMSE value generated with the proposed model for melanoma detection was least with 0.2476 and 0.542, respectively.

The main characteristic of a robust and reliable machine learning model is its ability to perform in a set of heterogeneous datasets. Various cancer datasets collected from UCI repository are aggregated and diagnosed with the proposed melanoma model to test its robustness, as observed in Table 5. As many as 12 different cancer datasets were collected and evaluated with the proposed model for its effectiveness. It was observed that almost every dataset gave a very impressive performance when validated against parameters like accuracy, precision, recall and f-score values. Lung cancer generated an optimum accuracy of 98.2%. The highest precision, recall and f-score value of 98.1%, 97.4% and 97.8% respectively were recorded with brain tumour data. The simple average

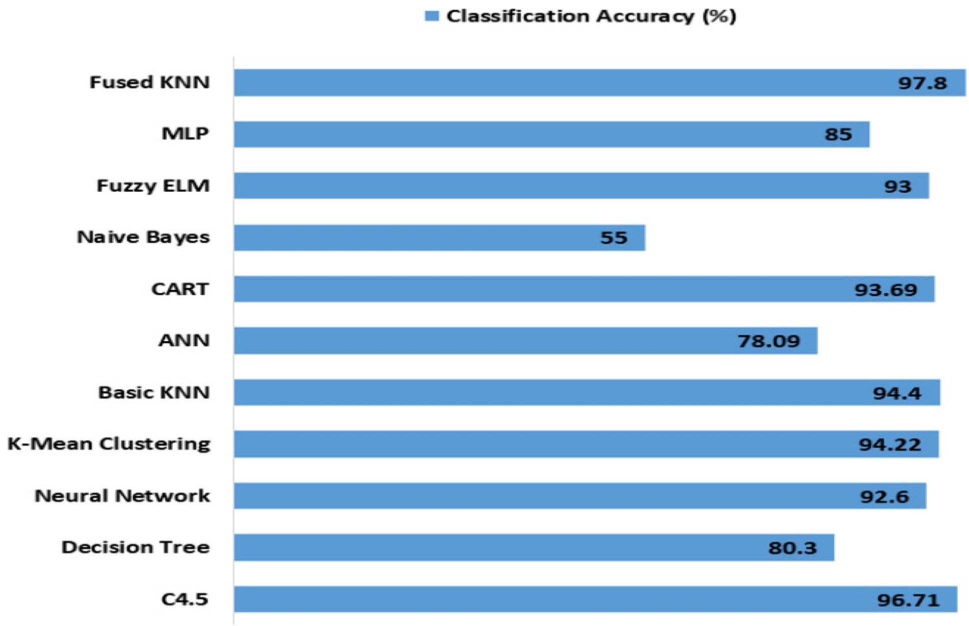

Figure 10. Classification accuracy analysis of IPS based fused-KNN model with other classifiers on melanoma data.

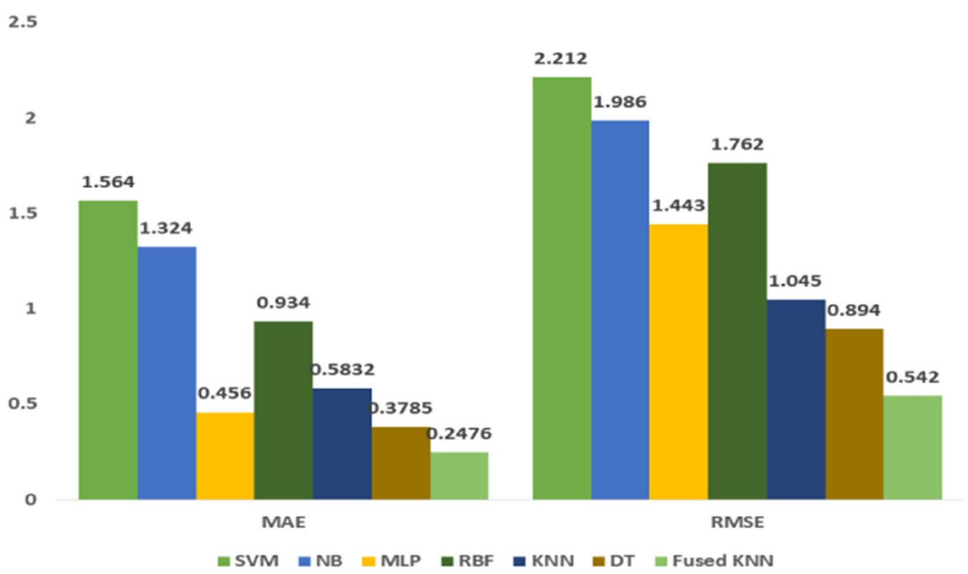

Figure 11. Error rate analysis of IPS based fused-KNN model with other classifiers on melanoma data samples.

mean value noted for accuracy, precision, recall and f-score was 94.45%, 95.2%, 94.4% and 94.9% respectively when validated with 12 cancer-based datasets.

Further analysis was carried out on melanoma dataset used in the study with the proposed model. The entire dataset was randomly partitioned into five distinct sub-samples with varying instances in every sample. The Individual sample was validated with different performance metrics to test its reliability and scalability. The Fused-KNN model was utilized in the process for validation. Sample 5 with 2600 instances generated a maximum accuracy of 98.1%. A precision value of 93.9% was noted with sample 3 comprising 2400 melanoma images. The Highest recall value of 92.7% was observed with sample 1 with 2100 images. The maximum f-score metric of 96% was noted with 2300 instances in sample 4 melanoma settings. In general, the mean accuracy, precision, recall and f-score value recorded were 97.8%, 93%, 92.46% and 93.66% respectively when evaluated with different samples of distinct melanoma images. The summarized results are highlighted in Table 6.

A shorter diagnostic time would come from automation using the recommended strategy during the skin monitoring step. Human labor is replaced with automation, which is less susceptible to human error.

Cancer Type	Accuracy(%)	Precision(%)	Recall(%)	F-Score(%)
Breast Cancer	96.5	96.4	96.1	96.2
Colon Cancer	97.5	97.2	96.5	96.8
Lung Cancer	98.2	97.7	97.3	97.5
Brain Tumor	97.4	98.1	97.4	97.8
Melanoma (Skin Cancer)	97.8	97.6	96.8	97.4
Liver Cancer	96.2	96.4	95.7	96.1
Prostrate Cancer	96.9	96.7	96.4	96.5
Colorectal Cancer	91	93	94	94
Oral Cancer	92	95	97	96.2
Thyroid Cancer	93	92	91	91
Lymphoma Cancer	96	91	93	91.5
Bladder cancer	93	91	92	91.4

Table 5. Performance metrics analysis of the proposed model with different cancer datasets.

Sample number and sample size	S1 (2100)	S2 (2200)	S3 (2400)	S4 (2300)	S5 (2600)	Mean value
Accuracy (%)	98	97.6	97.8	97.6	98.1	97.8
Precision (%)	91.8	93.7	93.9	91.9	93.7	93
Recall (%)	92.7	92	92	92.66	93	92.46
F-score (%)	95.33	92	91.66	96	93.33	93.66

Table 6. Performance metrics analysis of the proposed model with random heterogeneity samples.

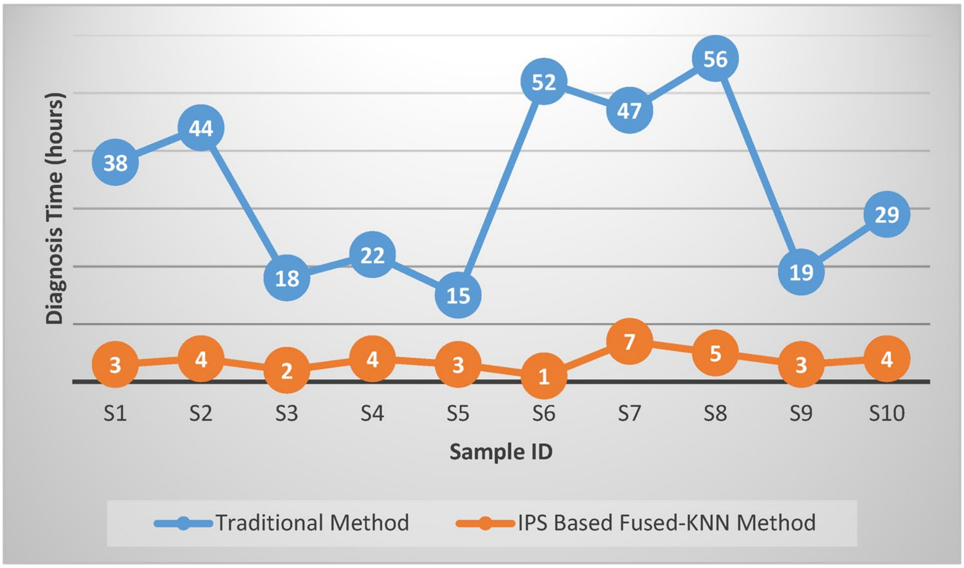

Figure 12. Depiction analysis of Manual vs. proposed system diagnosis time.

The comparison of manual versus suggested system diagnostic days is shown in Fig. 8. We discovered that the suggested approach significantly reduces diagnosing delays for doctors and patients. We conducted an experimental assessment using 10 healthy persons as actual time data. We executed the suggested procedure and then compared the results to the current manual system. As shown in Fig. 12, we found that the suggested approach is more effective than the current manual methodology. We found that this was the case because real-time access to the patient's medical information at the data centers allowed physicians to diagnose skin conditions. Through local or remote gateways, the sensors transfer actual time skin patient information or images to data centers. The proposed computer model assesses available data, describes the issue, and encourages a decision-making strategy that shortens the time required for diagnosis.

The mean from the manual approach comes out to be:

Mean (Manual Approach) = 34 h.
Mean (Proposed Model) = 3.6 h.

The Mean diagnosis time of the proposed model (3.6 h) is less than the Mean diagnosis time for manual approach (34 h), hence the days for the detection of melanoma is significantly less as compared to a manual approach. So using the IPS based Fused-KNN accuracy of detection of melanoma comes to be greater. The IPS based Fused-KNN consists of 3 folds, as we have 11,000 samples, splitting the folds will result in higher precision and recall value and hence results in higher accuracy of the model.

Since KNN is a lazy learner and needs no training period, it stores the training dataset and stores from it only. Since KNN takes less training time so the fusion of 3NN, 5NN, 7NN will provide a high accuracy analysis and better prediction and since this prediction of melanoma requires instant analysis hence the IPS based Fused-KNN is the most accurate classifier.

A comparative analysis of the accuracy of the proposed model is performed with other latest deep learning approaches and the outcome is shown in Fig. 13. Various advanced deep learning models like DenseNet, Mobile Net and VGG-19 were used in existing works for melanoma assessment. The model recorded a very promising performance recording a superior accuracy of 97.8%. Though many existing deep learning models gave good accuracy still model using DenseNet in[45] gave a relatively less accuracy of 76.09%. Use of NCC algorithm for noise reduction and feature extraction process helped in improving the overall accuracy of the proposed model.

The performance of a predictive model can be more reliable if it records promising result when tested with different datasets. The model is validated with 6 different melanoma datasets like PLCO, MNSIT and HAM among others[50–52]. It was observed that the model generated constructive outcome with all datasets. The mean accuracy, precision, recall and f-score were 95.95%, 95.01%, 93.7% and 94.4% respectively. The overall analysis is depicted in Fig. 14.

The latency delay criteria is very vital for any predictive model especially when applied in medical space. The training and testing delay is assessed with the model on different datasets. The mean training and testing delay computed was found to be 4 s and 1.5 s respectively. Figure 15 highlights the overall outcome.

With the advancement in technology, various emerging technologies are on rise which can be used in implementing IPS in the medical domain. A comparative analysis of such technologies is summarized in Table 7 along with their benefits and limitations.

In the study, IPS based predictive model for melanoma detection is successfully implemented but still some challenges exist in context to the study.

- The implementation of the proposed model using indoor positioning system for melanoma disease assessment is challenging because of the following factors:
- Architectural complication of indoor surrounding set up, presence of several obstacles inside medical centers and inconsistency in signal transmission speed make implementation difficult.
- Sometimes the quality of the input images received through the camera are less reliable which affects the accuracy of prediction.
- Sampling bias may occur due to ambiguity in sampling rate or clinical center location which affects the recorded sensor values. It affects the generalization of sensor readings.
- The scalability of the model is limited since with increase in patients and obstacles, the performance of the indoor positioning system may get affected sometimes.

The proposed indoor positioning system model in melanoma disease analysis can be successfully applied in future in following tasks:

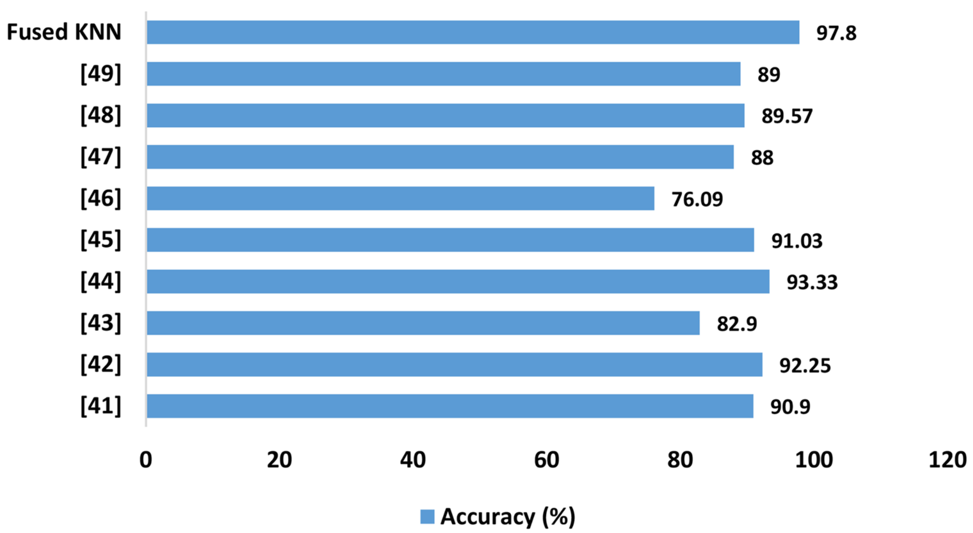

Figure 13. Comparative analysis of accuracy of latest deep learning models with proposed work.

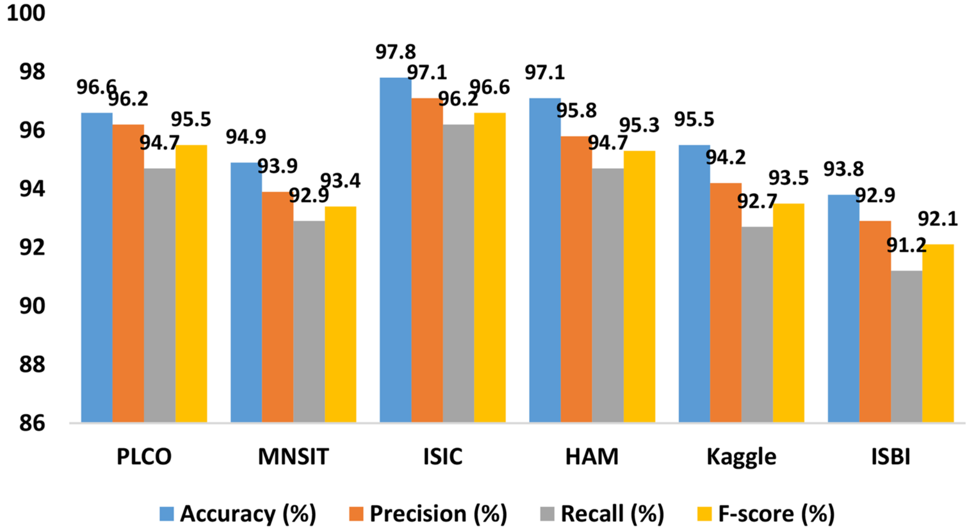

Figure 14. Performance of proposed model with different melanoma datasets.

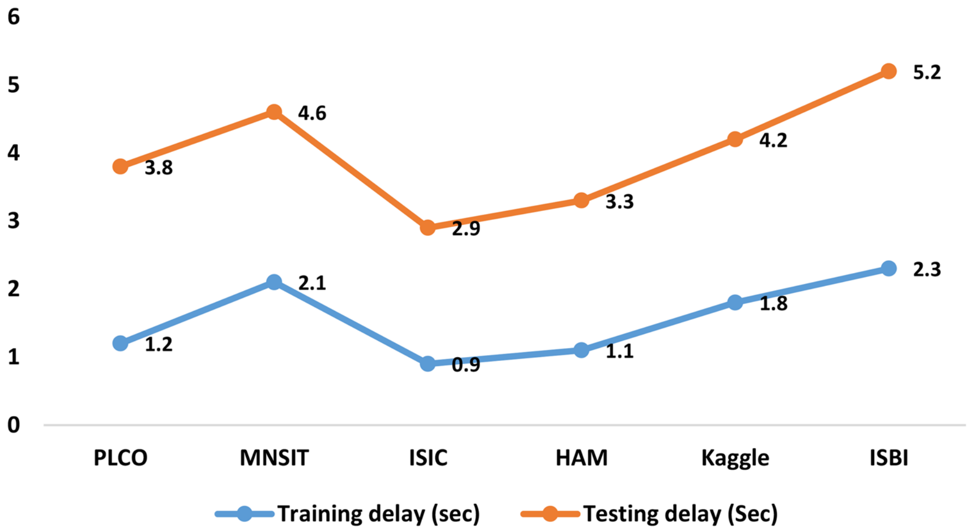

Figure 15. Latency delay analysis of proposed model using different melanoma datasets.

Technology	Benefit	Constraint
RFID	λ Line of sight between transmitter and receiver not needed. λ Quick and simultaneous scanning of multiple tags.	λ Less coverage with fluctuating signal. λ Restricted ability of non-active tags.
WLAN	λ Line of sight not needed. λ Reasonable scalability.	λ Complicated working principle λ Model restructuring needed with surrounding change.
Bluetooth	λ Better accuracy rate. λ Extra infrastructure not required.	λ Radio frequency interference. λ Coverage is very limited.
ZigBee	λ Less energy consumption	λ Requires sophisticated device set up. λ Risk prone due to interference by a several signals.
Infrared	λ Less energy wastage. λ Prevents multiple route effect.	λ Fails to penetrate walls. λ Needs line of sight. λ Short range signal transmission.
Ultrasound	λ Good accuracy. λ Unaffected by multiple routes.	λ Frequent interference by high-frequency signal. λ Signal loss for obstruction

Table 7. Modern technologies implementing IPS in medical sites.

- Effective scheduling consultation with medical experts to enable patients to take the optimum path feasible.
- Facilitate medical staffs in faster and accurately locating patients, professionals in emergency scenarios for proper diagnosis.
- Monitor vital clinical equipment and tools to minimize the probability of device loss.
- 3D sampling using shape and volume metrics, as well as an image optimization workflow for 3D image modeling, and the use of the Fused-KNN technique.

Conclusion

The indoor positioning system can be used in healthcare domains for the detection of various diseases. The IPS system works indoors involving the sensors and positioning system where GPS cannot work efficiently. Our research work involved the detection of skin cancer melanoma based on the IPS system. Using the IPS based system, sensors are used for the input sample from the patient automatically. In our model, we have used sensors such as CCD and CMOS camera sensors and IR as well as LIDAR for laser sampling. The images are processed using image processing methods such as image sampling, image restoration. The NCC algorithm was used in our model for detection of similarity in image samples from the camera and the laser sample. If the similarity is found, then the image overlapping method is used to get the final image, which is further processed for image noise reduction. The feature extraction process is done after the image has been optimized. In our research, we have introduced a new classifier, which is based on IPS and fusion of three variants of the KNN algorithm, which is termed as an IPS based Fused-KNN model. The IPS based Fused-KNN is used to classify the melanoma samples and determine the classification accuracy rate using the average mean accuracy of 3NN, 5NN and 7NN. The accuracy obtained with the proposed model is 97.8% which is much more than the existing classifiers that were studied in this work. The Simple average mean value noted for various performance indicators like accuracy, precision, recall, and f-score were 94.45%, 95.2%, 94.4% and 94.9% respectively when evaluated with 12 cancer-based datasets. The error rate analysis was also carried out to gauge the gap between the estimated value and real value. MAE and RMSE value outcome implementing a proposed model for melanoma classification was found to be very less with 0.2476 and 0.542 respectively. Thus, it can be concluded that the proposed IPS based intelligent framework with Fused-KNN approach can be an effective tool for precise detection and classification of melanoma disease diagnosis. It can be fruitful in assisting medical experts for quick, robust and reliable treatment of not only melanoma affected patients but also other cancer diseases. The future work includes the 3D sampling, which will use shape and volumetric metrics and the image optimization process for the 3D image sample and using the Fused-KNN technique.

Data availability

Data will be made available on request. For queries related to availability of the data, you may mail to Sushruta Mishra (sushruta.mishrafcs@kiit.ac.in).

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References

1. Thaajwer, M.A., & Ishanka, U.P. Melanoma Skin Cancer Detection Using Image Processing and Machine Learning Techniques. 2020 2nd International Conference on Advancements in Computing (ICAC). **1**, 363–368 (2020).
2. Yu, Z., Nguyen, J., Nguyên, T.D., Kelly, J., Mclean, C., Bonnington, P., Zhang, L., Mar, V.J., & Ge, Z. Early Melanoma Diagnosis With Sequential Dermoscopic Images. *IEEE Trans. Med. Imaging*. **41**, 633–646 (2021).
3. Davis, L.E., Shalin, S.C., & Tackett, A.J. Current state of melanoma diagnosis and treatment. *Cancer. Biol. Ther*. **20**, 1366–1379 (2019).
4. Alheejawi, S., Berendt, R., Jha, N., Maity, S.P., & Mandal, M. An efficient CNN based algorithm for detecting melanoma cancer regions in H&E-stained images. 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 3982–3985 (2021).
5. Gonçalo, G., & Helena, S. Indoor Location System Using ZigBee Technology. 2009 Third International Conference on Sensor Technologies and Applications, 152–157 (2009).
6. Banerjee, S., Pathak, A., Mishra, S., Vyas, S., de Albuquerque, V. H. C., & Reis, M. Skin Cancer Risks Estimation Using VGG19 Framework. In International Conference on Data Analytics & Management, 541–552 (Singapore, Springer Nature Singapore, 2023).
7. Palomo, A.M., Pérez, M.J., Pérez, O.R., Yabor, V.A., & Fontaine, A.M. Melanoma maligno cutáneo en pacientes de la provincia de Las Tunas. Revista Electrónica Dr. Zoilo E. Marinello Vidaurreta, **40** (2015).
8. Majumder, S., & Ullah, M.A. Feature Extraction from Dermoscopy Images for an Effective Diagnosis of Melanoma Skin Cancer. 2018 10th International Conference on Electrical and Computer Engineering (ICECE), 185–188 (2018).
9. ZooME Efficient Melanoma Detection Using Zoom-in Attention and Metadata Embedding Deep Neural Network Xiaoyan Xing; Pingping Song; Kai Zhang; Fang Yang; Yuhan Dong2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). In *Prominent Cancer Risk Detection Using Ensemble Learning. In Cognitive Informatics and Soft Computing* (eds Raghuwanshi, S. et al.) 677–689 (Springer, Singapore, 2022).
10. Ozturk, B. et al. Kutanöz malign melanomda adjuvan medikal tedavi yaklaşımları, *Türk Onkoloji Dergisi*, **25**, 170–180, (2010).
11. Wang, X., Huang, W., Lu, Z., & Huang, S. Multi-level Attentive Skin Lesion Learning for Melanoma Classification. 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 3924–3927 (2021).
12. Rehman, H., Adnan Shah, S., Ahmad, W., Anwar, S.M., & Nida, N. Deep retinanet for melanoma lesion detection. 2022 2nd International Conference on Digital Futures and Transformative Technologies (ICoDT2), 1–5 (2022).
13. Malyuskin, O., & Fusco, V.F. Resonance microwave reflectometry for early stage skin cancer identification. 2015 9th European Conference on Antennas and Propagation (EuCAP), 1–6 (2015)
14. Wollenberg, A. et al. Plasmacytoid dendritic cells: a new cutaneous dendritic cell subset with distinct role in inflammatory skin diseases. *J. Investig Dermatol.* **119**, 1096–1102 (2002).
15. Schmidt, E. & Zillikens, D. Modern diagnosis of autoimmune blistering skin diseases. *Autoimmun. Rev.* **10**, 84–89 (2010).

16. Wang, J. et al. Identification of unique proteomic signatures in allergic and non-allergic skin disease. *Clin. Exp. Allergy*. **47**, 1456–1467 (2017).
17. Sharma, P., Gautam, A., Nayak, R., & Balabantaray, B.K. Melanoma Detection using Advanced Deep Neural Network. 2022 4th International Conference on Energy, Power and Environment (ICEPE), 1–5 (2022).
18. Mahdiraji, S.A., Baleghi, Y., & Sakhaei, S.M. BIBS, a New Descriptor for Melanoma/Non-Melanoma Discrimination. Electrical Engineering (ICEE), Iranian Conference on, 1397–1402 (2018).
19. Chao, E., Meenan, C. K. & Ferris, L. K. Smartphone-based applications for skin monitoring and melanoma detection. *Dermatol. Clin.* **35**, 551–557 (2017).
20. Herfi Fani Martiano; Tito Waluyo Purboyo. Casi Setianingsih BIBS, a New Descriptor for 2019 6th International Conference on Instrumentation, Control, and Automation (ICA).
21. Thaajwer, M.A., & Ishanka, U.P. Melanoma Skin Cancer Detection Using Image Processing and Machine Learning Techniques. 2020 2nd International Conference on Advancements in Computing (ICAC). **1**, 363–368 (2020).
22. Albay, E., & Kamasak, M.E. Skin lesion classification using fourier descriptors of lesion borders. 2015 Medical Technologies National Conference (TIPTEKNO), 1–4 (2015).
23. Fidan, U., Sarı, İ., & Kumrular, R.K. Classification of skin lesions using ANN. 2016 Medical Technologies National Congress (TIPTEKNO), 1–4 (2016).
24. Baştürk, A., Yüksel, M. E., Badem, H. & Çalışkan, A. *Deep neural network based diagnosis system for melanoma skin cancer, in Signal Processing and Communications Applications Conference (SIU), 2017 25th,* 1–4 (2017).
25. Bui & Zorzi, M. Health care applications: a solution based on the internet of things, in Proceedings of the 4th International Symposium onApplied Sciences in Biomedical and Communication Technologies (ISABEL '11). (Barcelona, ACM, 2011).
26. McGrath, M.J., Scanaill, C.N. *Body-Worn, Ambient, and Consumer Sensing for Health Applications. In: Sensor Technologies*. (Apress, Berkeley). https://doi.org/10.1007/978-1-4302-6014-1_9 (2013).
27. Pantelopoulos, Bourbakis, N. G. & Part, C. *A survey on wearable sensor-based systems for health monitoring and prognosis, IEEE Transactions on Systems, Man and Cybernetics Applications and Reviews*, **40** (1), 1–12 (2010).
28. Swan Sensor mania! The internet of things, wearable computing, objective metrics, and the quantified self 2.0. *J. Sens. Actuator Networks*. **1** (3), 217–253 (2012).
29. Abidi, B., Jilbab, A. & Haziti, M. E. *Wireless sensor networks in biomedical: Wireless body area networks.In Europe and MENA Cooperation Advances in Information and Communication Technologies* 321–329 (Springer, Berlin/Heidelberg, 2017).
30. Xu, Q., Ren, P., Song, H. & Du, Q. Security enhancement for IoT communications exposed to eavesdroppers with uncertain locations. *IEEE Access*. **4**, 2840–2853 (2016).
31. Bgatova, N.P., Lomakin, A., Taskaeva, I.S., Obanina, N.A., Makarova, V., & Letyagin, A.Y. Structural Basis of Skin Melanoma Metastasis. 2022 Ural-Siberian Conference on Computational Technologies in Cognitive Science, Genomics and Biomedicine (CSGB), 340–342 (2022).
32. Chiuchisan, I., Costin, H., & Geman, O. Adopting the Internet of Things technologies in health care systems. 2014 International Conference and Exposition on Electrical and Power Engineering (EPE), 532–535 (2014).
33. Bhadula S, Sharma S, Juyal P, & Kulshrestha C. *Machine Learning Algorithms based Skin Disease Detection In 2019 International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN*. **9** (2), 2278–3075 (2019).
34. Gu, Y. & Tang, J. *A mobile system for skin cancer diagnosis and monitoring," SPIE Mobile Multimedia/Image Processing, Security, and Applications* (2014).
35. Ramlakhan, K. & Shang, Y. *A mobile automated skin lesion classification system, in ICTAI* (2011).
36. Giotis, I. et al. Med-node: a computer-assisted melanoma diagnosis system using nondermoscopic images. *Expert Syst. Appl.* **42** (19), 6578–6585 (2015).
37. Munia, T. T. K., Alam, M. N., Neubert, J. & Fazel-Rezai, R. *Automatic diagnosis of melanoma using linear and nonlinear features from digital image, in 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (2017).
38. Dreiseitl, S., Ohno-Machado, L., Kittler, H. & Vinterbo, S. Billhardt andM. Binder, a comparison of machine learning methods for the diagnosis of pigmented skin lesions. *J. Biomed. Inform.* **34** (1), 28–36 (2001).
39. Rubegni, P. et al. Digital dermoscopy analysis and artificial neural network for the differentiation of clinically atypical pigmented skin lesions: a retrospective study. *J. Invest. Dermatology*. **119** (2), 471–474 (2002).
40. Alwakid, G., Gouda, W., Humayun, M. & Sama, N. U. Melanoma Detection Using Deep Learning-Based Classifications. *Healthcare.***10**, 2481 (2022).
41. Kousis, I., Perikos, I., Hatzilygeroudis, I. & Virvou, M. Deep learning methods for accurate skin Cancer Recognition and Mobile Application. *Electronics*. **11**, 1294 (2022).
42. Fraiwan, M. & Faouri, E. On the automatic detection and classification of skin Cancer using deep transfer learning. *Sensors*. **22**, 4963 (2022).
43. Maniraj, S. & Maran, P. S. A hybrid deep learning approach for skin cancer diagnosis using subband fusion of 3D wavelets. *J. Supercomput*. **78**, 12394–12409 (2022).
44. Alam, M. J. et al. S2C-DeLeNet: a parameter transfer based segmentation-classification integration for detecting skin cancer lesions from dermoscopic images. *Comput. Biol. Med.* **150**, 106148 (2022).
45. Aljohani, K. & Turki, T. Automatic classification of melanoma skin Cancer with deep convolutional neural networks. *Ai*. **3**, 512–525 (2022).
46. Bechelli, S. & Delhommelle, J. Machine learning and deep learning algorithms for skin cancer classification from dermoscopic images. *Bioengineering*. **9**, 97 (2022).
47. Qasim Gilani, S., Syed, T., Umair, M., & Marques, O. Skin Cancer Classification Using Deep Spiking Neural Network. *J. Digit. Imaging*. **36**, 1137–1147 (2023).
48. Abdar, M. et al. Uncertainty quantification in skin cancer classification using three-way decision-based bayesian deep learning. *Comput. Biol. Med.* **135**, 104418 (2021).
49. Dua, D. & Graff, C. *UCI Machine Learning Repository* (2019) Available online: http://archive.ics.uci.edu/ml.
50. ISIC. : www.kaggle.com (2022) Dataset.
51. PLCO Dataset: www.kaggle.com.
52. MNIST Dataset: www.kaggle.com.

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Author contributions
Sushruta Mishra: Concept, methodology, and simulation setup. Himansu Das: Performed model implementation, validation, and prepared the original article. Sunil Kumar Mohapatra: Supervision . Surbhi Bhatia Khan: Review . Mohammad Alojail: Formal analysis . Mo Saraee: Review and drafting.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Additional information
Correspondence and requests for materials should be addressed to H.D. or S.B.K.

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