**Introduction:**

According to the World Health Organisation, skin cancer accounts for 33.33% of all cancer cases and is a growing worldwide health problem [1]. In countries such as the United States, Australia, and Canada, the incidence rate has risen considerably during the previous decade. Over 15,000 people die from skin cancer each year [2]. In the United States, just one kind of skin cancer claimed 7180 lives in 2021, and 7650 deaths from melanoma cancer are anticipated in 2022 [3]. In 2019, it is anticipated that 192,310 new melanoma cases would have been detected in only the United States, taking 7,230 fatalities. Although it is rather uncommon among the different. This kind of skin cancer is by far the most deadly. When recognised Melanoma has a 98% 5-year survival rate if detected early. However, as the illness spreads to organs and lymph nodes,5-year survival rates drastically decline, reaching 64% and 23%, respectively. Early detection is crucial [4]. Patients with stage I cancer, for instance, have an estimated 94% to 98% likelihood of overall survival after 10 years, whereas patients with stage IV disease have an estimated 10-year overall survival of just 10% to 15%. Some populations have a higher prevalence of melanoma than others. These high-risk situations can be avoided by being aware of these groups [5]. A dermoscopy, a specialised microscope that can alter lighting, distance, resolution, angle, and other aspects of image capture, is frequently used by doctors and dermatologists to make melanoma diagnoses. The ability to see the tiny structures of the epidermis and outer dermis is provided by dermoscopy pictures [6]. Machine learning is commonly employed in contemporary computer-based technology. It is a vast and quickly developing area of artificial intelligence that enables computers to autonomously learn and grow without needing to be explicitly programmed. [7]

Baldrick et al. contrasted professional judgement with artificial neural networks when categorising lesions. Dermatologists found equal sensitivity and specificity scores of 95% and 90%, respectively, whereas the computer programme claimed a sensitivity of 95% and a specificity of 88% [8]. These findings suggest that automated methods might be used in the fields of cancer detection

A largely supervised learning technique is used to predict cancer using classification algorithms based on conditional judgements or probabilities. Decision trees [9], convolutional neural networks (CNN), support vector machines (SVM), and k-nearest neighbours (KNN) are among the most widely used techniques or approaches.

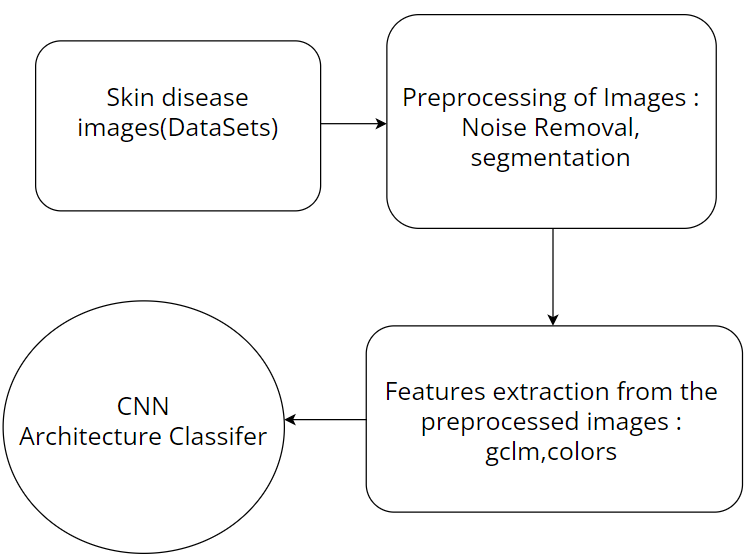
The use of these three algorithms in the search for skin cancer will be examined in this paper.

In contrast to traditional machine learning techniques, CNN is a deep learning approach that uses image processing algorithms and conclusions [10]. CNN models are effective at resolving complicated issues and produce output with great precision. They may be used with many mathematical learning techniques [11].

Regression and classification tasks are handled by support vector machines (SVMs) [12]. This method [6] use decision planes to establish decision boundaries. It utilises a labelled dataset for training as it is a supervised learning algorithm [13].

One of the simplest picture classification techniques is the k-nearest neighbour classifier. The main use of KNN is pattern recognition. This technique classifies unlabeled data points by locating the clusters with the most similarity among the k-closest examples.

This systematic review's objective was to assess the reliability and security of AI/ML technologies that could aid in the early diagnosis of skin cancer in primary and community care settings. The application of diagnostic algorithms to primary and community care (hence referred to as primary care), where the frequency of skin cancer is lower than in specialist clinics, is the topic of this Review, which was chosen on purpose. The first evaluation of the majority of worrisome skin lesions occurs in this context, hence this may be the area where AI/ML technologies can be most helpful. We looked at the quality of the available evidence, the stage of development the AI/ML technologies had reached, the gaps in the available evidence, and the potential for application in primary care.

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**Fig 1.1 –** Data flow diagram

**Literature Review:**

Skin cancer, notably melanoma, is a growing concern, particularly among young individuals[12], due to costly and delayed conventional diagnostic methods[13]. Artificial intelligence (AI) and deep learning have emerged as promising solutions. Previous research, including the use of models like VGG112, has shown the potential of AI in skin cancer detection[14,15]. This study combines VGG112 feature extraction with machine learning models like XGBoost and LightGBM, holding promise for accurate skin cancer classification and early diagnosis[14,16].

In the realm of skin disease detection, recent advancements in deep neural networks (DNNs) have significantly enhanced diagnostic reliability[17]. The ISIC 2019 dataset showcases the potential of DNNs, empowered by parallel processing and cloud computing[18]. Strategies like dimensionality reduction are crucial for handling irregularities in skin cancer datasets[19,21]. Densenet1129, guided by Bayesian optimization, demonstrates exceptional accuracy among various CNN architectures[16]. The PECK approach, which integrates deep networks, SVMs, and random forests, enhances boundary definition in challenging scenarios[20]. These innovations point towards a promising future of improved skin cancer diagnosis through deep learning, potentially leading to better patient outcomes[19].

**METHODOLOGIES:**

**DataSet For Research:**

**ISIC Archive Dataset :**

The ISIC Archive dataset contains around 23,000 pictures of skin issues, especially melanoma, an unsafe kind of skin sickness. These photographs Sourced from a collaborative effort of medical professionals, researchers. They're extraordinary quality. Experts looked at each picture and said if it's melanoma or not. This dataset is truly helpful for planning computers to check for melanoma, and it's a big deal in skin threatening development research. Notwithstanding, using it will in general be fascinating considering the way that there aren't various melanoma cases, and we ought to look out.

**Challenges in Gathering and Utilizing ISIC Dataset:**

**Data Irregularity:** The ISIC dataset, in the same way as other clinical datasets, experiences information unevenness, as malignant cases are relatively rare compared to benign ones. At the point when you select just a few pictures, guaranteeing a balanced portrayal in your training and testing datasets can challenge.

**Data Choice:** Picking the right subset of pictures to address both harmless(bengin) and dangerous cases(maligant) can be interesting. One-sided or deficient example determination might prompt one-sided computer based intelligence models.

**Data Augumentation:**

We can Augment our training data if necessary to increase the diversity of our dataset and improve model generalization. (Augmentation means rectifying the data imbalance and to avoid underfitting).There are many methods of augmentation like flipping ,rotating. We can also use Generative Adversial Network(GAW) to perform data augumentation.

**Generative Adversial Network (GAN):**It is a neural network architecture with 2 parts namely, generator, discriminator. Generator creates realistic looking images, discriminator distingushes between real and generated images.

Combine the original training dataset and the synthetic melanoma images generated by the GAN to create an augmented dataset. **A neural network called the Generator "G" produces fictional data "G" from noise "z.”[22]**

[log(D(x))] - [log(1 - D(G(z)))],

represents the loss function used in GANs, where D(x) is the discriminator's output when it evaluates real data (images), and D(G(z)) is the discriminator's output when it evaluates data generated by the generator from random noise z.

**Color Enhancement:** Enhancement technique based on the blue component of the RGB color channels is selected for the rest of processing which gives better results of both hair removal and segmentation**[23]**. we can find and distinguish hairlines in dermoscopic images. We do this by using a method called the "2-D derivatives of Gaussian" or DOG, focusing on the blue part of the images. It's like a special tool that helps us see lines of hair in four different directions. After we do this, we set a specific limit to separate the hairlines from the background in the image. It's kind of like drawing a clear line to say, "This is where the hair is, and this is everything else.

**Convolutional Neural Networks(CNNS):** The reception of Convolutional Brain Organizations (CNNs) has been a progressive move toward skin disease expectations. CNNs have to be trained using a huge dataset, This problem can be solved using the data augmentation. **We have used Traditional CNN for Skin Cancer Detection as mentioned in[24]** .CNNs are great at capturing skin lesions' intricate spatial hierarchies in medical images. The adoption of Convolutional Neural Networks (CNNs) has been a groundbreaking step in skin disease predictions. CNNs, such as VGG16, ResNet, and DenseNet, are employed as feature extractors and classifiers, enabling the automated identification of malignant skin lesions. These networks use convolution and pooling layers to extract relevant features from images, facilitating accurate classification.

**Transfer learning:**Transfer learning is a crucial technique for predicting skin cancer. Researchers can harness the vast knowledge stored in pre-trained CNN models, such as VGG16, ResNet-50, or DenseNet, which have been trained on large datasets like ImageNet. These pre-trained models have already learned to recognize general features such as edges, shapes, and textures. To adapt these models for the specific task of skin cancer classification, they can be fine-tuned using skin lesion datasets. This process is particularly valuable when working with limited labeled data since it significantly reduces the volume of data needed for training.

**VGG16, ResNet-50, or DenseNet For Feature Extraction:**

**The purpose of feature extraction is to reduce the number of features from images of the dataset.[25]** When we Load a pre-trained model e.g., VGG16 or ResNet50 **[26]**which involves using a neural network architecture that has already learned rich features from a large dataset. These pre-trained models are typically comprised of convolutional layers for feature extraction and fully connected layers for classification. To utilize these models for our own classification task, we remove the top classification layers, keeping only the feature extraction part. Then, you pass your augmented training data through these layers to extract abstract features from your images. These features are then flattened or reshaped into a format suitable for input to classifiers like XGBoost or LightGBM.

**Train XGBoost or LightGBM For Classification:**

**The most common way of preparing a XGBoost or LightGBM classifier includes utilizing the features extricated from your increased dataset as information. These elements basically address the significant data gained from our pictures.** Various AI draws near, such as SVM, KNN, Naive Bayes and others, are frequently used to distinguish between innocuous and cutaneous malignant melanoma injury**.[22] We take these component vectors and feed them into the classifier, which figures out how to make expectations in light of examples in the information.**

During training, the classifier fine-tunes its inner workings to reduce the gap between its predictions and the actual labels of the skin conditions. This means it gets better at understanding the relationships within the data, making it a reliable tool for predictions. In the end, you have a well-trained classifier that can be used to predict whether a new, unseen skin condition falls into the category of melanoma or not. This whole process is essential for your melanoma classification task.

**We are combining the techniques from both CNNs (for feature extraction) from [26] and ensemble learning for classification as in [27].** This approach leverages the strengths of each method: CNNs for feature extraction and XGBoost or LightGBM for making predictions based on those features. It's a powerful approach, especially when you have limited data or computational resources for training a full end-to-end deep neural network.

**Result:**

Recent advances in deep learning have demonstrated promising accuracy levels for skin cancer classification, rivaling dermatologist performance on select benchmarks. Key techniques include data augmentation, transfer learning, and uncertainty quantification.

Daghrir et al. [23] developed a hybrid approach combining multiple models - a convolutional neural network (CNN), support vector machine (SVM), and k-nearest neighbours (KNN) classifier. Their dataset contained 640 dermoscopic images resized to 224x224 pixels, split into 512 training and 128 testing images. The CNN architecture consisted of 3 convolutional layers with ReLU activation and 3x3 filters. It was trained for 10 epochs on the training data. The SVM used a radial basis function (RBF) kernel and the KNN was tested with k=5 nearest neighbours.

For feature representation, color, texture and border descriptors were extracted. Color features included 11 Color Name (CN) linguistic labels. Texture was captured using SIFT and HOG descriptors. Border features like convexity, circularity, and irregularity index described lesion shape. The CNN automatically learned feature representations from the pixel data.

Classification results showed 85.5% accuracy with the CNN model, 71.8% with SVM, and 57.3% with 5-NN. By ensembling all models via majority voting, the overall accuracy improved to 88.4%. This demonstrates the power of combining multiple models to boost performance compared to individual models.

Zunair and Hamza [28] also employed a deep CNN architecture but focused specifically on acral melanoma, a rare subtype occurring on palms and soles. Their network had 9 layers and was trained on an augmented dataset of 640 images from the ISIC archive, resized to 124x124 pixels. Data augmentation techniques like rotation, flipping, blurring, and GAN-generated samples were utilized to balance the class distribution.

The architecture consisted of 3 convolutional layers for feature extraction, followed by 3 max pooling layers for downsampling. Two dropout layers were also added for regularization to reduce overfitting. The pixel-level input images were 224x224 in size. Without augmentation, the CNN achieved 92.7% testing accuracy on the ISIC dataset. The sensitivity was 95.26% and specificity 87.89%, showing reliable detection of both malignant and benign lesions.

Both studies performed vital preprocessing steps like hair removal and lesion segmentation to isolate the skin lesions. Daghrir et al. used morphological snakes for segmentation whereas Zunair and Hamza adopted gradient filtering.

Rashid et al. [29] proposed a MobileNetV2 transfer learning model, trained on 11,670 augmented ISIC 2020 images. They achieved 98.2% average accuracy for melanoma classification, with 98.3% recall and 98.1% F1-score. Extensive augmentation handled class imbalance.

Abdar et al. [30] evaluated uncertainty methods like Monte Carlo dropout on ISIC 2019. Their hybrid model combining dropout and ensembling attained 89% accuracy and 0.91 F1-score, showing improved diagnosis.

Preprocessing steps are vital for isolating lesions. Hasan et al. [31] used blackhat filtering for hair removal and morphological snakes for segmentation. Alwakid et al. [32] employed GANs for data augmentation and segmentation to extract region of interest.

For features, Alenezi et al. [33] extracted color, texture and shape descriptors. CNNs automatically learn hierarchical representations, e.g., MobileNetV2 and NASNet . Transfer learning avoids overfitting on small medical datasets.

Model design focuses on accuracy and efficiency. Lightweight SqueezeNet reduced parameters for edge devices . Spiking neural networks enable low-power hardware execution. Stacked pipelines improve segmentation, feature extraction and classification, but can increase overhead.

Kousis et al. [34] evaluated 11 CNNs on ISIC 2019, finding DenseNet169 achieved 92.25% accuracy. Mazoure et al. [35] developed a web-based classifier attaining 100% melanoma prediction probability. These represent state-of-the-art benchmarks, but real-world validation on diverse patients is still lacking.

Factors like skin type, hair, lesions and image artifacts continue to challenge existing methods. Large-scale annotated datasets with varied characteristics are lacking, limiting model generalization. Class imbalance also skews performance, requiring techniques like oversampling.

Key trends include personalized model optimization, uncertainty-aware prediction, edge-focused lightweight designs, and clinically-guided system development. With sufficient data and validation, deep learning holds immense potential to enhance melanoma screening, aiding early diagnosis and saving lives. But effective real-world translation remains a research priority.

In the domain of skin disease characterization, the XGBoost Classifier with VGG16 as an element extractor stands apart for its exceptional exactness, with a sensitivity of 95.26% and an specificity of 87.89% [ 22]. However, for those focusing on quick model preparation and expectation, LightGBM with VGG16 ends up being a more proficient decision, offering a sensitivity of 96.84% and a specificity of 82.89%. This compromise among exactness and effectiveness highlights the significance of choosing the right classifier in view of the particular necessities of the application [22]**.**

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