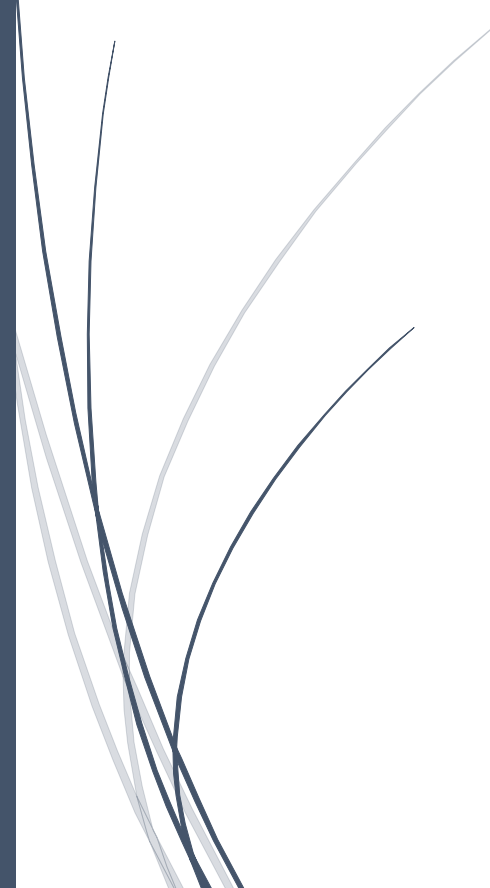


The logo for RADemics, featuring the text "RADemics" in white on a blue arrow-shaped background. The arrow points to the right and is part of a larger blue graphic element on the left side of the slide.

RADemics

Hybrid Deep Learning Models for Skin Cancer Detection through Dermoscopic Imaging

Several thin, curved lines in shades of blue and grey originate from the bottom left corner and sweep upwards and to the right, creating a decorative, organic feel.

S. Ram Prasath, Mohd Faiz Afzal
KAMARAJ COLLEGE OF ENGINEERING AND
TECHNOLOGY, AFZAL MULTI SPECIALITY CLINIC

Hybrid Deep Learning Models for Skin Cancer Detection through Dermoscopic Imaging

¹S. Ram Prasath, Assistant Professor, Department of CSE, Kamaraj College of Engineering and Technology, Madurai, Tamil Nadu, India. srpfxec@gmail.com

²Mohd Faiz Afzal, Homeopathic Consultant, (BHMS/DAFE/CNCC), Founder, (Afzal Multi speciality Clinic), Kongad-1, Palakkad, Kerala, India. mfabhms@gmail.com

Abstract

Early and accurate detection of skin cancer remains a critical challenge in dermatology, as malignant lesions often exhibit subtle visual patterns that are difficult to discern through conventional inspection. Recent advances in deep learning have enabled significant improvements in automated dermoscopic image analysis; standalone architectures frequently suffer from limitations such as data imbalance, lack of interpretability, and poor generalization across heterogeneous datasets. Hybrid deep learning models, which integrate convolutional neural networks with complementary machine learning or deep learning techniques, offer a promising solution to these challenges by enhancing feature representation, improving classification accuracy, and providing robust, context-aware predictions. This chapter presents a comprehensive exploration of hybrid architectures for skin cancer detection, encompassing CNN-SVM, CNN-LSTM, and CNN-Transformer frameworks. Key considerations such as data augmentation, preprocessing, attention-based feature refinement, and model evaluation metrics are discussed in detail. The integration of explainable AI techniques was emphasized to ensure clinical interpretability and foster trust in automated diagnostic systems. Comparative analyses of hybrid paradigms highlight their advantages in sensitivity, specificity, and generalization, while also addressing practical deployment considerations, including computational efficiency and adaptability to diverse dermoscopic datasets. By systematically bridging the gap between computational intelligence and clinical applicability, this work provides a framework for developing scalable, reliable, and interpretable automated skin cancer detection systems, contributing to enhanced early diagnosis and improved patient outcomes.

Keywords: Skin Cancer Detection, Hybrid Deep Learning, Dermoscopic Imaging, CNN, Attention Mechanisms, Explainable AI

Introduction

The early detection of skin cancer was of paramount importance due to its rapidly increasing global incidence and the significant mortality associated with melanoma [1]. Skin cancer encompasses a range of malignancies, including basal cell carcinoma, squamous cell carcinoma, and melanoma, with melanoma accounting for the majority of skin cancer-related deaths despite being relatively less prevalent [2]. The prognosis for melanoma was heavily dependent on the stage at which it was diagnosed, highlighting the critical need for accurate and timely diagnostic methodologies [3]. Conventional diagnostic approaches, such as visual examination and histopathological assessment, require specialized expertise and are susceptible to variability

among clinicians [4]. These methods are often invasive, time-consuming, and may not be feasible for mass screening initiatives, particularly in resource-constrained environments. The increasing volume of dermoscopic images captured in modern dermatology clinics underscores the necessity for automated diagnostic systems that can provide rapid, accurate, and scalable assessments, minimizing human error while improving patient outcomes [5].

Dermoscopic imaging has emerged as a non-invasive and highly effective tool for skin lesion evaluation, offering enhanced visualization of subsurface structures that are not visible to the naked eye [6]. Dermoscopy enables the observation of pigmentation patterns, vascular networks, and morphological irregularities, which are essential indicators of malignancy [7]. The manual interpretation of dermoscopic images was labor-intensive and requires significant clinical expertise, resulting in variability in diagnostic accuracy [8]. Studies have demonstrated that even experienced dermatologists may exhibit differing sensitivity and specificity when evaluating similar lesions, particularly in cases of early-stage melanoma or atypical presentations [9]. This variability emphasizes the need for automated systems capable of consistent interpretation across diverse datasets. The increasing demand for teledermatology and remote diagnosis presents further challenges, as models must generalize effectively to images captured under varying conditions and by different imaging devices, necessitating sophisticated computational approaches capable of handling such heterogeneity [10].

Deep learning has revolutionized medical image analysis, offering unprecedented capabilities in automated feature extraction and classification [11]. Convolutional neural networks (CNNs), in particular, have shown remarkable proficiency in learning hierarchical representations directly from raw images, outperforming traditional handcrafted feature-based approaches in multiple dermatological tasks [12]. Standard CNN architectures, including ResNet, DenseNet, and EfficientNet, have demonstrated high accuracy in distinguishing between benign and malignant skin lesions [13]. These advancements, conventional CNNs face several limitations. These models often require large annotated datasets to prevent overfitting and may struggle with class imbalance, which was prevalent in skin cancer datasets due to the relative rarity of malignant lesions [14]. CNNs lack inherent interpretability, which raises concerns regarding their clinical adoption and trustworthiness. Variations in lesion morphology, lighting conditions, and image acquisition further complicate their performance, highlighting the necessity for hybrid strategies that can integrate complementary computational paradigms to achieve both accuracy and generalizability [15].