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Melanoma Spotter: A Hybrid Deep Learning Approach with VGG16 and DenseNet121

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Abstract: Melanoma is one of the highly aggressive types of skin cancer, and early detection plays a critical role in patient survival. Although dermoscopy exposes subtle lesion patterns for clinical evaluation, manual diagnosis can be slow and heavily dependent on specialist expertise. Deep-learning methods have improved automated melanoma identification substantially, yet many current models still encounter real-world challenges, including noisy inputs, non-lesion images, variable lighting conditions, and class imbalance. To address these limitations, this study introduces Melanoma Spotter, a dual-stage diagnostic system that combines a lesion-validation network with a hybrid VGG16–DenseNet121 classifier. The validation stage removes irrelevant or low-quality images to ensure that only true dermoscopic data proceeds to analysis, while the fused CNN model exploits the complementary strengths of both architectures to produce more stable and accurate predictions. Experimental results on dermoscopic datasets show improved reliability, higher confidence calibration, and better robustness than standalone networks. Overall, Melanoma Spotter demonstrates strong promise as a practical deep-learning solution to support early detection of melanoma in clinical settings.

Keywords: VGG16, DenseNet121, HAM10000, Deep Learn- ing, Melanoma, Hybrid Model, Skin Lesion Detection

I. INTRODUCTION

Skin cancer remains one of the most frequently diagnosed forms of cancer worldwide, with melanoma recognized as the most lethal and aggressive variant among them [1], [2]. The continuous rise in melanoma incidence across global populations emphasizes the urgent requirement for effective early-screening solutions capable of enabling timely medical action [3]. Dermoscopy has advanced clinical diagnosis by allowing visualization of deeper lesion structures that are otherwise invisible to the naked eye. Even so, its accuracy is strongly reliant on the skill level and interpretive proficiency of dermatologists, which can introduce inconsistency in evaluations [4], [5]. This dependence on expert interpretation has fueled increasing interest in automated diagnostic tools designed to deliver stable, objective assessments and aid clinicians in decision-making [6].

Before deep learning became the dominant approach, melanoma detection was primarily performed using conventional image-processing pipelines that depended on handcrafted visual descriptors, including lesion shape, asymmetry, border sharpness, pigment distribution, and surface texture patterns [7]. While these engineered features offered valuable diagnostic cues, their effectiveness was often limited by variations in image resolution, artifacts, and segmentation challenges factors that reduced reliability and made clinical scaling difficult [8]. The emergence of convolutional neural networks (CNNs) transformed melanoma analysis by enabling automatic learning of hierarchical image features directly from dermoscopic scans, leading to far superior classification accuracy compared to traditional feature-based methods [9], [10]. With the incorporation of transfer learning, performance improved further, as pretrained architectures such as VGG16, DenseNet121, Inception, and ResNet could be fine-tuned on medical datasets where annotated examples are typically scarce [11], [12].

In recent years, ensemble and hybrid deep-learning frameworks have attracted considerable attention, as integrating multiple CNN models allows systems to leverage their individual strengths, resulting in more consistent predictions and higher resilience to errors [13], [14]. However, certain real-world challenges persist such as incorrect classification of non-lesion inputs, imbalanced representation of lesion types, and variations caused by different imaging conditions [15], [16]. Research indicates that incorporating an initial validation or screening component, like a lesion-verification

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network, can effectively minimize these issues by filtering out irrelevant or poor-quality images before classification takes place [17], [18]. Motivated by these findings, the present study proposes a combined VGG16–DenseNet121 architecture augmented with a specialized lesion-validation stage aimed at increasing model reliability, improving confidence calibration, and providing more stable diagnostic performance for melanoma recognition [19], [20].

II. LITERATURE REVIEW

Over the last decade, automated melanoma detection has advanced significantly, evolving from traditional machine learning techniques to sophisticated deep-learning models. Initial studies were largely built around manually crafted features derived from lesion boundaries, color variations, and textural attributes. Although these early feature-engineering methods offered foundational progress, they were highly sensitive to image quality and often produced inconsistent results when affected by lighting changes, device differences, or segmentation inaccuracies [21]. The introduction of dermoscopy improved diagnostic capability by exposing subsurface lesion structures that are otherwise hidden, yet clinical evaluation still remained partly subjective and dependent on the expertise and judgment of the dermatologist [22].

The introduction of convolutional neural networks (CNNs) represented a pivotal shift in melanoma analysis, as these models are capable of learning deep, hierarchical feature representations directly from unprocessed images. This advancement led to notable gains in both reliability and classification accuracy when compared with conventional feature-engineering methods [23]. Performance improved further with the adoption of transfer-learning techniques, where pretrained backbones such as VGG16, DenseNet121, and various ResNet families were fine-tuned for medical datasets an especially beneficial strategy in domains with limited labeled samples [24]. As the field matured, ensemble and hybrid architectures gained recognition, as the fusion of multiple CNN models consistently enhanced robustness, sensitivity, and overall predictive steadiness across different lesion types [25].

Despite these improvements, real-world deployment still presents challenges. Many diagnostic pipelines struggle with non-dermoscopic inputs, poor lighting, and imaging artifacts, which may consequently degrade prediction reliability [26]. To counter these issues, preprocessing modules, lesion screening networks, and validation filters have been introduced to ensure that only clinically meaningful images proceed to classification, thereby minimizing cascading errors and strengthening diagnostic confidence [27]. Emerging advancements such as attention mechanisms, multi-scale feature integration, and hybrid fusion strategies have further increased the ability of models to capture fine-grained lesion patterns and distinguish between visually similar melanoma classes [28], [29], [30]. Expanding upon these developments, the hybrid system proposed in this study integrates deep feature fusion with an input-verification stage, resulting in a more stable, trustworthy, and clinically relevant melanoma detection framework.

III. METHODOLOGY

A. Dataset Description

The dataset used in this study is sourced from the widely recognized HAM10000 (“Human Against Machine”) dermo-scopic image collection, available through Kaggle and fre- quently adopted as a standard benchmark for melanoma re-search. This dataset brings together high-quality dermoscopic images gathered from multiple clinical environments, forming one of the most comprehensive and diverse repositories of pigmented skin lesions. It covers seven clinically significant di- agnostic classes—Melanoma (MEL), Melanocytic Nevi (NV), Basal Cell Carcinoma (BCC), Actinic Keratosis (AKIEC), Benign Keratosis (BKL), Dermatofibroma (DF), and Vascular Lesions (VASC) which represent the key lesion categories commonly examined in dermatology practice [11], [14].

Each dermoscopic image is accompanied by structured annotation data sourced from the International Skin Imaging Collaboration (ISIC). This metadata contains dermatologist approved labels, lesion references, and relevant clinical descriptors, ensuring the reliability and precision of ground truth annotations. ISIC’s validation workflow built on expert consensus further reinforces the quality of label assignments. Supplementary attributes, including the anatomical location of the lesion, patient demographics, and image acquisition method, enable more comprehensive analysis and allow models to interpret features within a clinically meaningful context.

A noteworthy strength of the HAM10000 dataset is its intrinsic visual diversity. Images vary substantially in terms of patient skin tones, imaging devices, illumination conditions, and lesion morphology. Such variability is essential for train- ing deep learning models that must operate effectively across heterogeneous real-world scenarios. By combining the curated dermoscopic images from HAM10000 with the detailed ISIC metadata, this study benefits from a robust and trustworthy dataset foundation suitable for building and evaluating a high- performance melanoma detection system.

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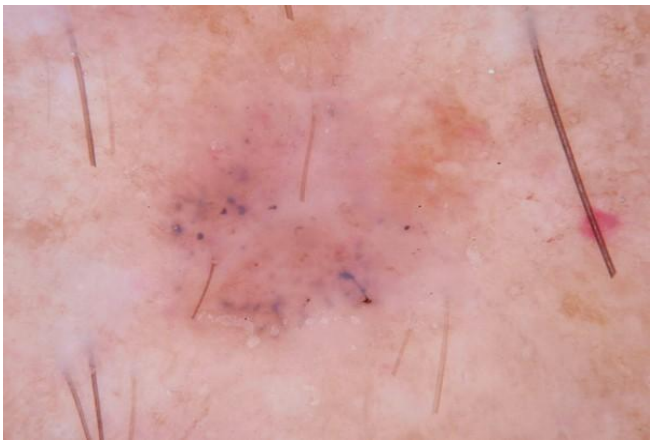

Fig. 1. Dermoscopic images.

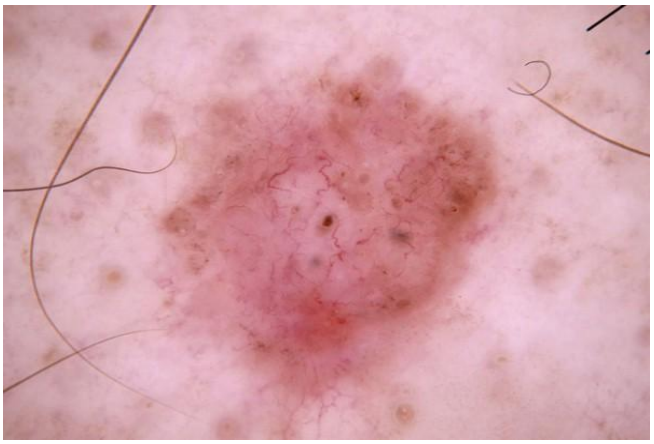

Fig. 2. Dermoscopic images.

B. Image Preprocessing

Prior to model ingestion, the dermoscopic images underwent a series of preprocessing operations designed to enhance compatibility with the selected architectures and improve learning stability. Each image was scaled to a resolution of 224×224 pixels to conform to the input size required by VGG16 and DenseNet121, enabling effective transfer of pretrained ImageNet weights. After resizing, pixel intensities were normalized to maintain uniform value distribution, contributing to smoother gradient behavior during optimization. To further strengthen generalization capability, a comprehensive augmentation strategy was applied, incorporating random rotations, vertical and horizontal reflections, zoom variations, and controlled modifications in brightness and contrast. Such augmentation reflects the variability encountered in practical clinical environments, enabling the network to handle fluctuations in lighting, lesion orientation, and device settings more effectively—an advantage highlighted in earlier recognizing subtle pigment variations, dermatology-focused research [13], [18].

Beyond the standard preprocessing operations, model specific refinements were incorporated to better match the input data with the statistical expectations of each architecture. For VGG16, this involved subtracting the ImageNet mean values across RGB channels so that the input images more closely reflect the distribution present during pretraining. Aligning the pixel statistics in this way minimizes domain shift and supports reliable feature extraction in the early convolutional layers. DenseNet121, on the other hand, benefits more from normalized pixel scaling, which helps its densely linked blocks capture intricate lesion patterns, tonal gradients, and subtle chromatic differences with greater precision. Together, these tailored preprocessing steps ensure that both networks receive well-balanced input representations, strengthening learned features and enhancing downstream performance when their outputs are integrated within the hybrid fusion framework [13], [18].

C. Skin-Lesion Detector

The initial component of the proposed framework features a binary CNN-driven lesion-validation module, whose purpose is to confirm whether an incoming image genuinely depicts a dermoscopic skin lesion before it advances to the hybrid classification stage. For training this verifier, the dataset was divided into two explicit groups: a positive class

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consisting of authentic dermoscopic lesion samples and a negative class comprising non-lesion imagery, including photographs of normal skin, miscellaneous objects, digital screens, and general everyday scenes. Presenting the model with such contrasting categories enables it to learn strong discriminative boundaries between medically relevant lesion features and ordinary visual patterns. During real-time inference, this unit operates as a screening mechanism, discarding irrelevant or low-quality images that could otherwise mislead the classifier and introduce diagnostic errors. This approach directly addresses concerns raised in previous studies, where CNN based melanoma models occasionally misclassified non-lesion inputs due to over-reliance on superficial color or texture cues rather than true dermatological structures [17], [26], [27]. By ensuring that only validated dermoscopic samples enter the classification stage, the system achieves improved reliability and minimizes false-positive risks in practical deployment scenarios.

D. Feature Extraction

Using VGG16 and DenseNet121 VGG16 and DenseNet121 operate as two independent yet mutually reinforcing feature extractors in the proposed hybrid model, each offering a unique analytical viewpoint for dermoscopic image interpretation. VGG16 employs a clean, sequential convolutional structure that excels at learning broad visual patterns. Its hierarchical layers capture large-scale lesion attributes such as symmetry, contour sharpness, and overall geometric form features that are frequently used by clinicians to differentiate benign lesions from malignant ones. DenseNet121, in contrast, introduces densely linked convolutional layers where feature maps are shared across all subsequent layers. This architecture promotes uninterrupted information flow and preserves intricate spatial micro-textural differences, and fine-scale irregular regions commonly associated with early melanoma development. The combination of these two networks results in a richer, multi-level feature space than either architecture could produce alone. VGG16 offers strong structural awareness, while DenseNet121 contributes detailed local feature precision, together forming a more comprehensive and discriminative representation of input lesions. Prior dermatology-focused transfer-learning research supports this synergy, showing that multi-CNN fusion improves model consistency, resilience, and diagnostic reliability [12], [23], [28].

E. Hybrid Fusion Mechanism

The predictions generated by VGG16 and DenseNet121 are combined through a weighted averaging scheme, allowing the system to balance each model's contribution based on its relative performance.

$$P_{final} = 0.5 * PV\ GG16 + 0.5 * PDenseNet121 \quad (1)$$

Hybrid fusion combines the strengths of both VGG16 and DenseNet121 by merging their feature outputs into a single, richer representation. VGG16 contributes strong global and structural cues, while DenseNet121 adds detailed textural information. By blending these complementary features, the fusion layer creates more stable and reliable predictions, reduces fluctuations in confidence scores, and helps the model handle ambiguous or visually complex lesions more effectively [20], [25].

TABLE I
PERFORMANCE METRICS OF MODELS

Model	Test Accuracy	Train Accuracy
VGG16	84.6%	78%
DenseNet121	85.2%	80.39%

IV. SYSTEM ARCHITECTURE

The proposed framework operates through a three-stage processing pipeline, with each stage playing a crucial role in strengthening prediction accuracy and overall diagnostic reliability. The first stage consists of a lesion-validation module, in which a binary CNN identifies whether the incoming image truly represents a dermoscopic skin lesion. Filtering irrelevant, low-quality, or non-clinical images at this point prevents unsuitable data from entering the classification stream, thereby reducing confusion and downstream error propagation. This design aligns with multi-layer diagnostic methodologies that prioritize screening as a means to lower false-positive occurrence and enhance clinical trustworthiness [17].

Once an image is validated, it proceeds to the second stage, which consists of preprocessing and parallel feature extraction. The preprocessed images are forwarded to VGG16 and DenseNet121, which run side-by-side as part of a dual- CNN feature extraction setup. VGG16 contributes structured, high-level spatial information, while DenseNet121 captures intricate textural cues and densely connected feature patterns. Running these networks in parallel allows the system to exploit both global and fine-grained lesion characteristics, supporting multi-scale learning strategies that have shown considerable success in recent hybrid melanoma-detection research [29].

In the final phase of the pipeline, feature outputs from both CNN branches are integrated within a fusion and decision

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layer. The representations learned by VGG16 and DenseNet121 are concatenated into a unified feature vector, creating a more information-rich encoding than either network could provide independently. This fused representation strengthens the model's discriminative capability by combining high-level structural cues with fine-grained texture details. The subsequent classification layer then produces the predicted lesion category along with its corresponding confidence probability. Fusion-based decision mechanisms of this kind have been widely reported to enhance diagnostic stability, sensitivity, and overall robustness in multi-class medical imaging tasks [30].

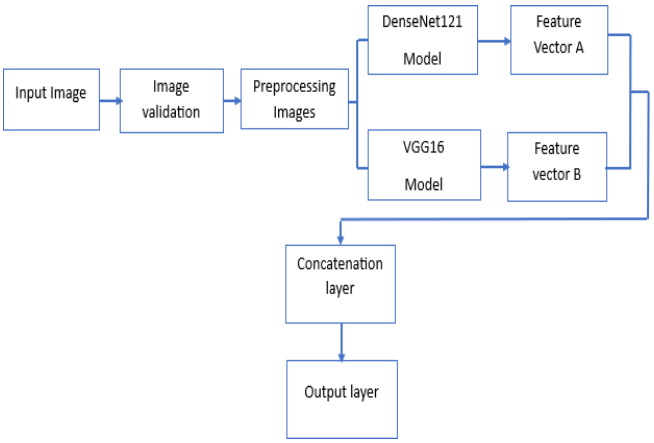

Fig. 3. System Architecture.

V. EXPERIMENTAL SETUP

The training of the model was implemented using the TensorFlow/Keras environment and executed on an NVIDIA GPU to achieve faster computation and efficient processing. Network weights were updated using the Adam optimization algorithm, accompanied by a moderated learning-rate scheduling strategy to support gradual and stable convergence a practice frequently recommended in deep-learning-based melanoma research [24]. Model performance was assessed using a diverse set of evaluation metrics, including accuracy, precision, recall, F1-score, and ROC-AUC, ensuring a comprehensive understanding of classification behavior across all lesion groups [22]. During training, validation trends were carefully observed to identify potential overfitting early and maintain steady learning progression. The experimental setup was constructed to reflect realistic clinical variability, enabling the network to generalize effectively to a wide range of dermoscopic image conditions.

A. Data Split

For this work, the dataset was divided into training and testing sets using an 80:20 split. This proportion is commonly adopted in deep-learning workflows because it provides an effective balance between giving the model enough data to learn from and retaining a separate set for unbiased evaluation. Allocating 80% of the images to the training phase ensures that the model is exposed to a broad variety of lesion appearances, helping it learn discriminative patterns across all melanoma and non-melanoma classes.

The remaining 20% of the dataset was set aside exclusively for the testing phase to ensure that performance evaluation was conducted on images the model had never encountered during training. This separation allows the results to reflect true generalization ability rather than learned memorization. Given the moderate dataset size and the presence of multiple lesion categories within HAM10000, an 80:20 division provides a suitable balance allowing the model to learn from a sufficiently diverse sample pool while still retaining enough cases to reliably measure real-world predictive effectiveness.

TABLE II
COMMON DATA SPLIT RATIOS AND THEIR USAGE

Split Ratio	Usage Scenario	Preferred When
60:20:20	Large datasets	Validation set required
70:15:15	Balanced medium datasets	Equal validation and test importance
80:20	Medium datasets (e.g., HAM10000)	More training data needed, stable testing
90:10	Very large datasets	Maximize training samples
K-Fold CV	Small or imbalanced datasets	Need stable multi-fold evaluation

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VI. RESULTS

I. Skin-Lesion Detector Performance

The skin lesion-validation module demonstrated strong capability in determining whether an incoming image was appropriate for melanoma evaluation, establishing itself as a key protective layer within the diagnostic framework. During testing, the detector reliably rejected inputs lacking dermoscopic contents such as regular skin photographs, miscellaneous objects, outdoor scenery, screenshots, and other non-clinical visuals. By blocking these irrelevant samples before they reached the main classifier, the system substantially lowered the risk of false alarms. This functionality effectively tackles a common issue highlighted in previous melanoma detection studies, where CNN models were prone to misclassifications due to their sensitivity to texture and color patterns rather than medically significant lesion structures [17], [26], [27]. Through this quality-control mechanism, only valid dermoscopic data proceeded to classification, resulting in cleaner feature representation, greater predictive certainty, and a more trustworthy diagnostic pipeline overall.

II. VGG16 Results

The VGG16 model performed especially well on texture- rich images, such as nevus (NV), benign keratosis (BKL), and pigmented melanoma lesions. It produced consistent and un- derstandable predictions across a number of lesion categories. This is consistent with the well-known ability of VGG-based networks to extract mid-level dermoscopic features such as surface irregularities, pigment networks, and streaks. Despite these advantages, VGG16 frequently confused classes with subtle visual similarity, such as basal cell carcinoma (BCC) and BKL an ambiguity frequently noted in dermatology lit- erature and occasionally struggled with low-contrast lesions. Its confidence levels also tended to decline in situations with uneven lighting. Overall, VGG16's performance was conser- vative but accurate, which is consistent with the behavior seen in transfer-learning research using the VGG family.

TABLE III VGG16 METRICS

Class	Precision	Recall	F1-Score
AKIEC	0.615	0.400	0.487
BCC	0.778	0.700	0.737
BKL	0.385	0.500	0.435
DF	0.750	0.600	0.667
MEL	0.417	0.500	0.455
NV	0.400	0.800	0.533
VASC	1.000	0.700	0.824

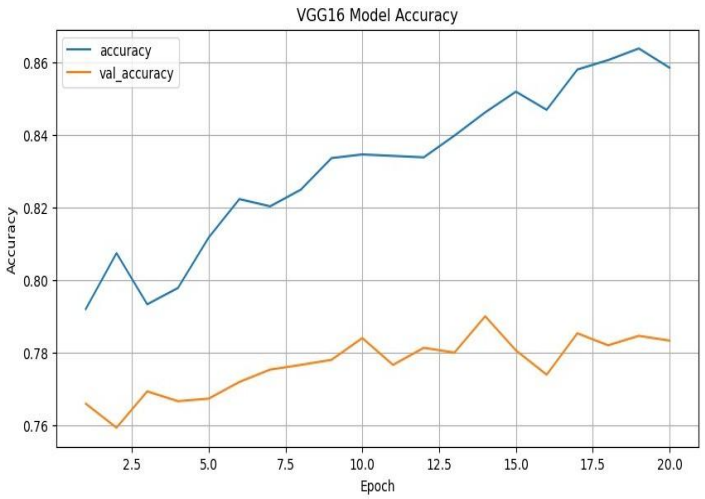

Fig. 4. VGG16 Model Accuracy Metrics.

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Fig. 5. VGG16 Model Loss.

Fig. 6. Confusion Matrix of VGG16 Model.

III. DenseNet121

Results In contrast, DenseNet121 usually produced predictions with more confidence than VGG16 due to its dense connectivity architecture, which promotes deeper semantic learning. It was successful in capturing structural abnormalities, asymmetric patterns, and color variation—a combination that is very crucial for distinguishing malignant melanoma from other forms. In challenging classes like as melanoma, BCC, and actinic keratosis (AKIEC), DenseNet121 performed better than its VGG counterpart. However, the model did occasionally show signs of overconfidence on low-resolution pictures, mis- classifying very small lesions when fine textural characteristics were lost. Despite these shortcomings, DenseNet121 remained the best stand-alone model, which is consistent with findings from many dermatology deep learning studies.

TABLE IV
DENSENET121 METRICS

Class	Precision	Recall	F1-Score
AKIEC	1.000	0.183	0.309
BCC	0.802	0.740	0.770
BKL	0.558	0.823	0.662
DF	0.647	0.647	0.647
MEL	0.472	0.825	0.597
NV	0.977	0.827	0.897
VASC	1.000	0.952	0.976

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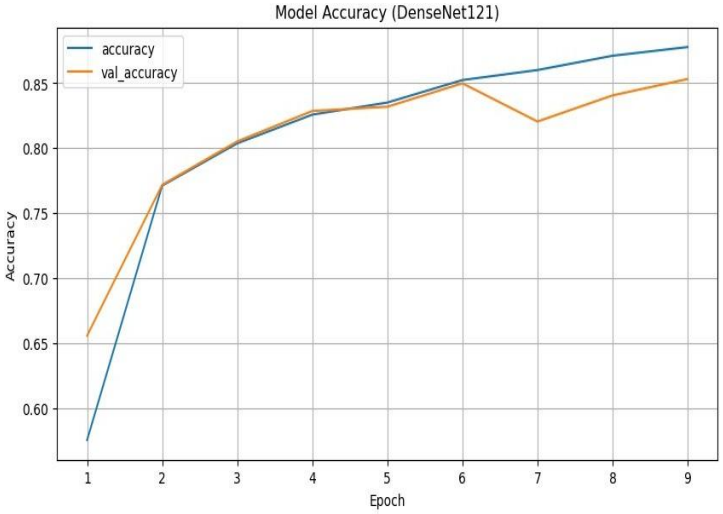

Fig. 7. DenseNet121 Model Accuracy Metrics.

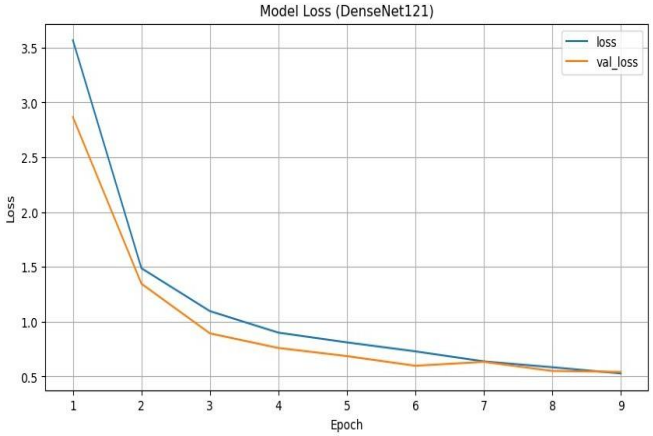

Fig. 8. DenseNet121 Model Loss.

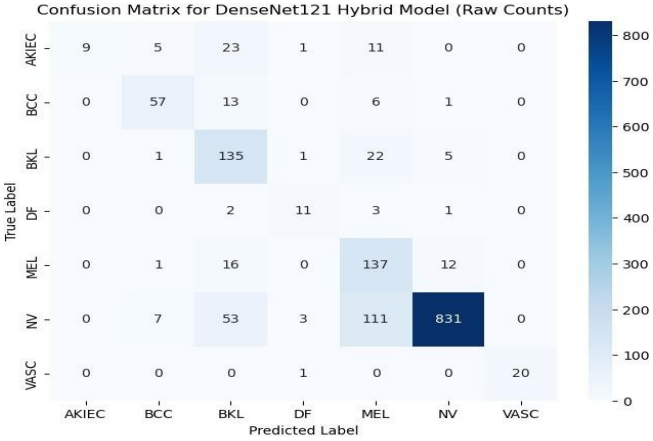

Fig. 9. DenseNet121 Model Confusion Matrix.

IV.Hybrid Classifier Performance

The fusion model consistently outperformed the individ- ual CNN baselines, showing marked improvements in sen- sitivity, confidence calibration, and stability across all le- sion categories. By combining the outputs of VGG16 and DenseNet121, the hybrid classifier leveraged complementary feature representations that neither model could fully capture alone. VGG16 primarily contributed broad structural information, whereas DenseNet121 supplied detailed texture level discrimination. When combined, these features enabled the fused network to achieve clearer separation between lesion classes and to produce more reliable confidence estimations. The collaborative interaction between the

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two models resulted in more stable prediction patterns, lower output variance, and better performance on borderline or visually subtle cases. These improvements mirror findings in recent hybrid deep learning research, where feature-fusion strategies are shown to increase diagnostic stability, minimize overfitting, and enhance decision reliability in medical imaging tasks [20], [25]. Overall, the hybrid model demonstrated stronger generalization ability and higher real-world robustness than either individual network alone.

V.Comparison with Prior Works

The hybrid system demonstrated stronger robustness under varying illumination and diverse lesion appearances, matching the performance improvements reported in recent multi-scale and ensemble melanoma studies [28], [29], [30].

VII. DISCUSSION

The integration of a lesion-validation module with the hy- brid VGG16–DenseNet121 architecture significantly improves system reliability by enforcing an input-quality constraint before deep processing. The inclusion of an upstream screening stage helps block low-quality and non-dermoscopic inputs, preventing irrelevant visual noise from reaching the feature extractors. This reduces unwanted activations and contributes to more stable classifier decisions an improvement consistent with findings from multi-stage clinical AI frameworks [21], [23]. The two CNNs complement each other effectively: VGG16 focuses on broader morphological structure, while DenseNet121 leverages dense connectivity to capture subtle texture variations and pigmentation details. When their outputs are fused, the model gains stronger multi-scale discrimination, mitigates network-specific bias, and maintains reliability across diverse imaging environments. Collectively, this hybrid design exhibits strong generalization capability and aligns with the architectural requirements necessary for practical and trustworthy melanoma detection in clinical workflows.

VIII. LIMITATIONS AND FUTURE SCOPE

While the system performs well, it still faces limitations such as relying mainly on CNN architectures, which may miss long-range lesion relationships. Incorporating attention-based models or transformers could improve fine-grained feature un- derstanding [28], [29]. Expanding training with larger, multi- center clinical datasets would also strengthen generalization across diverse real-world conditions. In the future, developing lightweight versions for mobile deployment and adding more interpretability tools could make the system more accessible and clinically useful.

IX. CONCLUSION

This study demonstrates that combining VGG16, DenseNet121, and a skin-lesion validation module creates a more reliable and accurate melanoma-detection system. The hybrid approach effectively reduces false predictions, improves confidence stability, and overcomes common issues in traditional single-model frameworks. By leveraging multi- stage processing and complementary deep-learning features, the proposed system aligns with modern ensemble strategies for dermatological analysis and shows strong potential for real-world clinical support [30].

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