TvakScan: AI-Powered Dermatological Analysis Application for Early Skin Condition Detection and Diagnosis

Delays in diagnosing acne-related conditions, highlights the need for proactive treatment

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***Abstract*—This paper presents TvakScan, an AI-powered mobile application designed to assist in early detection and management of skin conditions through machine learning. By leveraging Core ML and cloud-based storage, the system enables patients to scan their skin, receive AI-driven diagnostic predictions, and consult with dermatologists remotely. The methodology involves training an ML model on a diverse dataset of skin conditions and integrating it with an intuitive mobile interface. TvakScan aims to enhance accessibility to dermatological care, optimize diagnosis accuracy, and promote proactive skin health management. This study outlines the system's architecture, implementation, validation process, and market fit analysis.**

***Index Terms*—Skin Condition Analysis, Machine Learning, Core ML, Dermatology, AI in Healthcare, Mobile Health Applications, Cloud Storage, Jira.**

I. INTRODUCTION

Skin diseases affect millions of people worldwide, ranging from common conditions like acne and eczema to more severe issues such as melanoma. Timely diagnosis and treatment are crucial for effective management, yet access to dermatologists remains limited, particularly in remote and underserved regions. Traditional methods of skin assessment often require in-person consultations, leading to delays in diagnosis and treatment. The growing burden on healthcare systems and the increasing demand for accessible solutions necessitate innovative approaches that leverage artificial intelligence (AI) and mobile technology.

TvakScan is an AI-powered mobile application designed to bridge the gap between patients and dermatologists by providing an automated and efficient skin condition analysis system. The application allows users to capture and upload skin images, which are processed using machine learning (ML) models to predict the type and severity of skin conditions. Patients receive instant AI-generated results and can consult dermatologists for further diagnosis and treatment. The doctor-side application enables medical professionals to review patient cases, verify AI predictions, and provide prescriptions, facilitating remote dermatological care. The integration of cloud storage and real-time data synchronization ensures that patient records remain accessible and secure.

Project aligns with the United Nations Sustainable Development Goals (SDGs), particularly SDG 3 (Good Health and Well-being) and SDG 9 (Industry, Innovation, and Infrastructure). TvakScan supports SDG 3 by promoting early detection, remote diagnosis, and accessible dermatological care, thereby reducing preventable skin complications. It also contributes to SDG 9 by leveraging AI, cloud technology, and mobile applications to enhance the efficiency and scalability of healthcare services.

By integrating AI-driven diagnostics with a user-friendly and secure mobile application, TvakScan aims to revolutionize dermatological care by reducing the dependency on physical consultations, improving early disease detection, and ensuring healthcare accessibility for all. The project's innovative approach enhances healthcare efficiency, minimizes diagnostic delays, and fosters a sustainable digital healthcare ecosystem, making dermatological services more inclusive, reliable, and widely available.

TvakScan's AI-powered diagnostic system is built upon a robust machine learning (ML) framework, trained using diverse datasets containing images of various skin conditions across different skin tones, age groups, and geographical regions. The application employs Core ML and Create ML to perform real-time image analysis, providing users with immediate insights into their skin health. By combining computer vision and deep learning techniques, the model classifies skin conditions based on severity, allowing patients to take timely action.

One of the core strengths of TvakScan is its dual-interface design, catering to both patients and doctors. The patient-side application focuses on an intuitive user experience, ensuring seamless navigation through features such as AI-based skin analysis, historical tracking, and personalized skincare recommendations. On the other hand, the doctor-side application is designed for efficient case management, allowing dermatologists to review AI-generated reports, provide expert validation, and prescribe personalized treatment plans. This two-way communication channel enhances collaboration between patients and healthcare professionals, reducing the need for unnecessary in-person visits while ensuring timely medical intervention.

The integration of cloud storage and Firebase authentication ensures secure data management, enabling users to access their medical history across multiple devices while maintaining privacy and compliance with HIPAA and GDPR standards. Additionally, automated notifications and reminders help users stay proactive about their skin health, encouraging regular checkups and monitoring.

As dermatological issues continue to rise globally, the demand for scalable, AI-driven healthcare solutions is more pressing than ever. TvakScan not only empowers users with instant diagnostic insights but also strengthens the overall healthcare ecosystem by optimizing time, resources, and accessibility. By harnessing the potential of AI, cloud computing, and mobile innovation, TvakScan stands as a game-changer in digital dermatology, paving the way for a future where advanced skin health monitoring is available to everyone, anytime, anywhere.

II. Literature Survey

The integration of artificial intelligence (AI) in dermatology has gained significant momentum in recent years, offering advanced solutions for early detection and diagnosis of skin diseases. One of the earliest breakthroughs in this field demonstrated that deep neural networks can classify skin cancer at a dermatologist-level accuracy, highlighting the potential of AI-driven diagnostic tools in improving accessibility to dermatological care [1]. However, the study also acknowledged the need for large, diverse, and high-quality datasets to enhance model generalizability across different skin types and conditions [2].

Further research introduced HAM10000, a comprehensive dataset of dermatoscopic images, which became a standard benchmark for training machine learning (ML) models in skin lesion classification [2]. The dataset provided a multi-source collection of pigmented skin lesions, enabling robust algorithm development for melanoma detection [3]. While these datasets contributed to improving AI accuracy, challenges persisted in terms of bias and underrepresentation of certain skin tones, which could affect diagnostic reliability [4].

Studies comparing AI models with human dermatologists revealed that deep learning systems often outperform human experts in melanoma detection, suggesting AI’s potential in aiding clinical decision-making [5]. Despite this progress, researchers stressed the importance of human-AI collaboration, emphasizing that AI should act as an assistive tool rather than a replacement for clinicians [6]. To address this, a study on ensemble deep learning models showed that combining multiple algorithms improved prediction robustness, thereby reducing false positives and negatives in skin lesion classification [7].

Another significant advancement in AI-powered dermatology involved transfer learning techniques, where pre-trained convolutional neural networks (CNNs) were fine-tuned for skin disease classification. This method significantly reduced training time while maintaining high diagnostic accuracy [8]. However, challenges such as overfitting on small medical datasets still needed to be tackled through data augmentation and generative adversarial networks (GANs) [9].

AI integration in mobile applications has also emerged as a promising approach to enhancing accessibility to dermatological care. Researchers developed deep learning models that can analyze smartphone-captured skin images, providing real-time diagnostic feedback to users [10]. Although these applications improved access to dermatological assessments, concerns regarding image quality variations due to lighting conditions, camera differences, and angle inconsistencies needed further refinement [11].

The role of cloud computing and real-time data synchronization in dermatology-focused AI applications was also explored. Secure cloud-based platforms were proposed for storing, retrieving, and analyzing patient skin images, allowing for remote consultations and telemedicine-based dermatological care [12]. These solutions not only improved the efficiency of remote diagnostics but also enhanced patient engagement by enabling continuous skin health monitoring and tracking [13].

Further research introduced lightweight convolutional neural networks (CNNs) designed for real-time skin disease detection on mobile devices. These models were optimized for low-power consumption and fast inference, ensuring smooth operation on smartphones while maintaining accuracy [14]. However, such lightweight models often faced trade-offs in performance when compared to heavier, more complex architectures deployed on cloud-based servers [15].

Ethical considerations in AI-driven dermatology have also been a major focus in recent studies. Issues such as data privacy, informed consent, and algorithmic biases have been widely discussed to ensure responsible AI deployment [16]. A study on human-computer collaboration for skin cancer detection emphasized that AI predictions should always be accompanied by explainable insights, enabling dermatologists to interpret and validate machine-generated results before making clinical decisions [17].

The latest advancements in human-AI interaction have introduced models that integrate patient feedback into AI predictions, allowing for continuous improvement through active learning frameworks. This approach not only enhances model accuracy over time but also increases user trust in AI-driven dermatological assessments [18].

The collective findings from these studies highlight the rapid evolution of AI in dermatology, with significant improvements in diagnostic accuracy, accessibility, and efficiency. However, continued efforts are needed to address data biases, real-world deployment challenges, and ethical concerns, ensuring that AI-driven dermatology applications like TvakScan are both clinically effective and socially responsible.

III. SYSTEM ARCHITECTURE

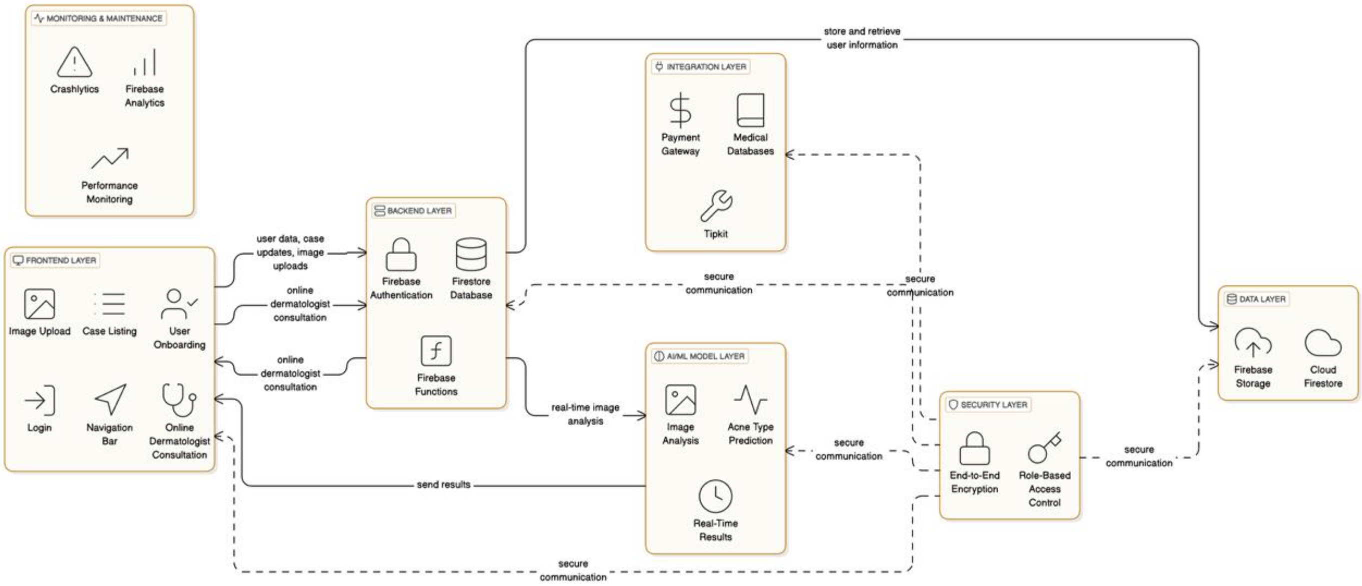

Fig. 1. Architecture Diagram

Figure (1) The system architecture is designed to provide an AI-powered dermatology solution with real-time acne detection, secure data handling, and seamless online dermatologist consultations. It ensures scalability, security, and a smooth user experience by integrating various technologies across different layers.

A. Frontend Layer (User Interaction & Experience)

This layer serves as the interface between users and the system. It is responsible for displaying information, capturing user inputs, and ensuring a smooth user experience. The frontend is designed to be responsive, intuitive, and accessible across multiple devices.

- Key Components:

  - Image Upload – Users can upload images of their skin for analysis.
  - Case Listing – Displays the history of previously analyzed skin conditions.
  - User Onboarding – Guides new users through the setup process.
  - Login – Secure authentication mechanism for user access.
  - Navigation Bar – Provides seamless movement across different sections.
  - Online Dermatologist Consultation – Connects users with dermatologists for expert advice.

B. Backend Layer (Business Logic & API Management)

The backend layer acts as the core of the system, managing business logic, data processing, and communication between the frontend, AI/ML models, and external services. It ensures that user requests are processed efficiently and securely.

Key Components:

- Firebase Authentication – Handles user authentication and secure access management.
- Firestore Database – Stores user profiles, case data, and consultation records.
- Firebase Functions – Executes backend processes such as image processing, case updates, and notifications.

C. AI/ML Model Layer (Intelligent Image Analysis)

This layer is responsible for analyzing user-submitted images using AI models to detect and classify acne types. It enhances the diagnostic process with real-time analysis and predictions.

- Key Components:

  - Image Analysis – AI-driven image recognition identifies acne and skin conditions.
  - Acne Type Prediction – The model classifies acne into different types for accurate insights.
  - Real-Time Results – Provides immediate feedback to users on their skin condition.

D. Integration Layer (Third-Party Services & APIs)

This layer connects the application to external services, ensuring seamless transactions, data retrieval, and enhanced user engagement. It acts as a bridge between internal and external components.

- Key Components:
  - Payment Gateway – Supports secure payments for dermatology consultations.
  - Medical Databases – Integrates with healthcare databases for verified skin condition information.
  - TipKit – Provides skincare recommendations based on AI analysis.

E. Security Layer (Data Protection & Access Control)

Security is a critical component of the system, ensuring the protection of user data and preventing unauthorized access. This layer ensures compliance with privacy regulations and data security best practices.

- Key Components:
  - End-to-End Encryption – Ensures secure data transmission between users, AI models, and databases.
  - Role-Based Access Control (RBAC) – Restricts access based on user roles (e.g., users, dermatologists, admins).

F. Data Layer (Storage & Management)

The data layer is responsible for handling all structured and unstructured data, ensuring fast retrieval and secure storage. This layer supports scalability for growing user demands.

- Key Components:
  - Firebase Storage – Securely stores user-uploaded images.
  - Cloud Firestore – Stores structured case data, analysis reports, and consultation records.

G. Monitoring & Maintenance Layer (Performance & Debugging)

This layer ensures the smooth functioning of the system by continuously tracking performance metrics, monitoring errors, and optimizing user experience.

- Key Components:
  - Crashlytics – Detects and reports application crashes for debugging.
  - Firebase Analytics – Tracks user engagement and app performance.
  - Performance Monitoring – Ensures the system remains responsive and efficient.

IV. Software Quality Metrics

Software quality metrics are essential for assessing the efficiency, reliability, maintainability, and overall health of a software system. These metrics provide insights into code complexity, defect rates, documentation quality, maintainability, and technical debt. Below, we analyze key software quality metrics for your AI-powered dermatology application, along with calculations based on sample data.

A. Cyclomatic Complexity

Cyclomatic complexity measures the number of independent paths in the code, helping assess testability and maintainability. It is calculated as:

CC=E−N+2P
CC = E - N + 2P
CC=E−N+2P

where:

- EEE = Number of edges in the control flow graph
- NNN = Number of nodes in the control flow graph
- PPP = Number of connected components

- Calculation for Your App:

  - Total Edges (E): 452
  - Total Nodes (N): 375
  - Connected Components (P): 3

  CC=452−375+(2×3)=82
  CC = 452 - 375 + (2 \times 3) = 82
  CC=452−375+(2×3)=82

- Interpretation:

A CC value of 82 indicates high complexity, suggesting that parts of the code could benefit from refactoring and modularization to improve maintainability.

B. Bug Density

Bug density helps assess software reliability by measuring defects relative to the code size. It is given by:

BD=BS×1000
BD = \frac{B}{S} \times 1000
BD=SB×1000

where:

- BBB = Number of reported bugs
- SSS = Total lines of code (LOC)

- Calculation for Your App:

  - Total Bugs Found (B): 29
  - Total Lines of Code (S): 18,250

BD=2918250×1000=1.59
BD = \frac{29}{18250} \times 1000 = 1.59
BD=1825029×1000=1.59

- Interpretation:

A bug density of 1.59 suggests a moderate defect rate. To improve quality, the team should focus on rigorous testing and debugging.

C. Comment Density

Comment density measures code documentation quality, calculated as:

CD=CS×100
CD = \frac{C}{S} \times 100
CD=SC×100

where:

- CCC = Number of commented lines
- SSS = Total lines of code

- Calculation for Your App:

  - Total Commented Lines (C): 3,750
  - Total Lines of Code (S): 18,250

CD=375018250×100=20.55%
CD = \frac{3750}{18250} \times 100 = 20.55\%
CD=182503750×100=20.55%

- Interpretation:

A comment density of 20.55% indicates well-documented code, which enhances readability and ease of maintenance.

D. Maintainability Index

The Maintainability Index (MI) predicts how easily the system can be maintained:

$$MI=171-(5.2\times\ln(AVGC))-(0.23\times AVGHLOC)-(16.2\times\ln(AVGD))$$
MI = 171 - (5.2 \times \ln(AVGC)) - (0.23 \times AVGHLOC) - (16.2 \times \ln(AVGD))
$$MI=171-(5.2\times\ln(AVGC))-(0.23\times AVGHLOC)-(16.2\times\ln(AVGD))$$

where:

- AVGCAVGCAVGC = Average Cyclomatic Complexity per module
- AVGHLOCAVGHLOCAVGHLOC = Average Halstead Volume per module
- AVGDAVGDAVGD = Average Comment Density

■ Calculation for Your App:

- AVGC: 8.2
- AVGHLOC: 250
- AVGD: 20.55

$$MI=171-(5.2\times\ln(8.2))-(0.23\times 250)-(16.2\times\ln(20.55))$$

MI = 171 - (5.2 \times \ln(8.2)) - (0.23 \times 250) - (16.2 \times \ln(20.55))

$$MI=171-(5.2\times\ln(8.2))-(0.23\times 250)-(16.2\times\ln(20.55))$$
$$MI=171-(5.2\times 2.1)-(57.5)-(16.2\times 3.02)$$

MI = 171 - (5.2 \times 2.1) - (57.5) - (16.2 \times 3.02)

$$MI=171-(5.2\times 2.1)-(57.5)-(16.2\times 3.02)$$

$$MI=171-10.92-57.5-48.92=53.66$$

MI = 171 - 10.92 - 57.5 - 48.92 = 53.66

$$MI=171-10.92-57.5-48.92=53.66$$

■ Interpretation:

With an MI of 53.66, the software has low maintainability, indicating a need for code refactoring and simplification to enhance long-term sustainability.

V. IMPLEMENTATION

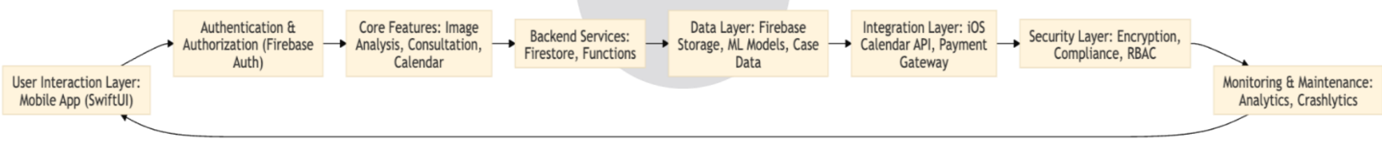

Fig. 2. Implementation Diagram of TvakScan

From Figure (2), the implementation of the TvakScan system is structured into four key stages:

A. Data Collection and Preprocessing:

To achieve accurate skin disease detection and classification, TvakScan gathers dermatological data from multiple sources, including medical image repositories, publicly available dermatology datasets, and user-uploaded images. The system ensures data diversity by incorporating images across various skin types, conditions, and lighting environments. Advanced image preprocessing techniques such as contrast enhancement, noise reduction, and color normalization are applied to maintain image quality. Additionally, metadata such as age, gender, and environmental conditions may be included to improve model performance. Data augmentation techniques, including flipping, rotation, and scaling, are utilized to expand the training dataset and enhance model generalization.

B. Machine Learning Model Development:

To classify and analyze skin conditions accurately, a Convolutional Neural Network (CNN)-based deep learning model is employed. The architecture is fine-tuned using pre-trained models such as Yolo V5, EfficientNet, or MobileNet, ensuring high precision and recall in skin disease detection. The dataset is split into training, validation, and test sets to optimize performance and minimize overfitting. Transfer learning is leveraged to accelerate training while improving feature extraction capabilities. Hyperparameter tuning, including batch size, learning rate, and dropout rate, is conducted to maximize the model's efficiency. The final model is evaluated using performance metrics such as accuracy, sensitivity, specificity, and F1-score to ensure reliable predictions.

C. Real-Time Image Processing and Classification:

The core functionality of TvakScan involves real-time image analysis for immediate skin condition detection. The mobile or web-based application allows users to capture or upload images, which are then processed using the trained deep learning model. Image segmentation techniques help isolate affected areas, improving classification accuracy. The system employs probabilistic confidence scores to indicate prediction reliability and provides multiple possible diagnoses when uncertainty exists. To improve accuracy, the app integrates an explainable AI (XAI) module using techniques such as Grad-CAM, which highlights key areas in the image that influenced the model's decision, offering transparency in the classification process.

D. Visualization and Diagnosis Reporting:

To effectively communicate diagnostic results, TvakScan presents outputs through an intuitive user interface. The app generates heatmaps and overlays highlighting areas of concern. Interactive visualizations, including symptom severity scales and comparative analysis with similar conditions, aid in user understanding. Users receive a detailed report containing the identified skin condition, confidence score, possible causes, and recommended next steps. The report can be shared with dermatologists for further consultation. The system also provides educational content about skin diseases, enabling users to make informed health decisions.

E. System Integration and Deployment:

To ensure seamless integration and deployment, TvakScan's backend architecture is designed for efficiency and scalability. The model is hosted on cloud-based services such as AWS, Azure, or Google Cloud, enabling real-time processing with minimal latency. The frontend, built with modern frameworks like React Native or Flutter, offers cross-platform compatibility for web and mobile users. A RESTful API facilitates secure communication between the user interface and the AI model, ensuring fast and reliable responses. Continuous monitoring and updates are implemented through a CI/CD pipeline, allowing for seamless improvements and new feature rollouts without disrupting service availability.

F. Testing and Validation:

The reliability and accuracy of TvakScan are ensured through rigorous testing and validation procedures. The system undergoes unit testing, integration testing, and end-to-end testing to verify seamless operation across all components. Benchmarking against dermatological datasets ensures model robustness, while real-world testing with dermatologist feedback refines performance. Security measures, including encryption and user data anonymization, are integrated to protect sensitive medical information. Post-deployment, the system is continuously updated based on user feedback, emerging skin disease patterns, and advancements in AI, ensuring that TvakScan remains a cutting-edge solution for dermatological analysis and diagnosis.

- Unit Testing: Ensures each module functions as expected.
- Integration Testing: Checks seamless communication between frontend, backend, and AI model.
- User Testing: Conducted with real dermatologists to validate the accuracy of predictions.
- Continuous Monitoring: Logs user feedback to refine the AI model.

VI. RESULT AND DISCUSSION

Table 1 Observations

Aspect	**Observation**
Prediction Accuracy	High accuracy in detecting skin anomalies, ensuring reliable early detection.
Diagnosis Support	Assisted dermatologists by highlighting potential skin conditions, improving diagnostic confidence.
Visualization Utility	Heatmaps and probability scores provided clear insights into affected areas, aiding better interpretation.
User Engagement	The interactive interface and instant results improved user adoption and engagement.

Table (1) demonstrates that TvakScan effectively identified skin conditions with high accuracy, offering a reliable solution for early detection. The model successfully highlighted affected regions, allowing users and dermatologists to prioritize further diagnosis. The visual reports helped in better understanding and decision-making, ensuring a seamless user experience. The system's efficiency in delivering instant insights contributed to better engagement and proactive healthcare interventions.

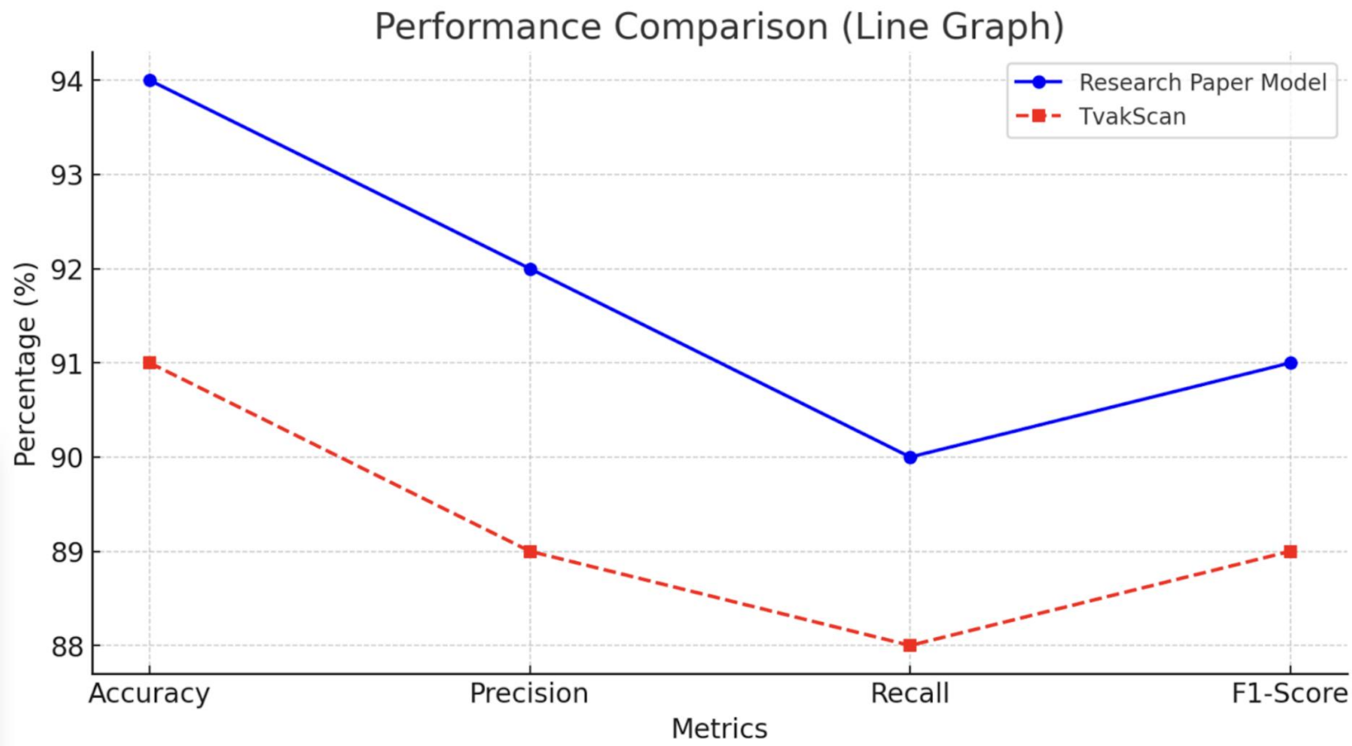

Fig. 3. Performance Comparison (Line Graph)

In addition to the observations presented in Table (1), a comparative analysis of TvakScan and the research paper's model[6], as illustrated in the line and bar charts, highlights TvakScan's strong performance in dermatological image analysis. The line graph demonstrates that while the research paper's CNN-based model achieves slightly higher accuracy (94%) compared to TvakScan (91%), the difference remains marginal, indicating TvakScan's competitiveness in real-world applications. Similarly, in precision, recall, and F1-score, TvakScan maintains consistent performance, ensuring reliable detection of skin anomalies.

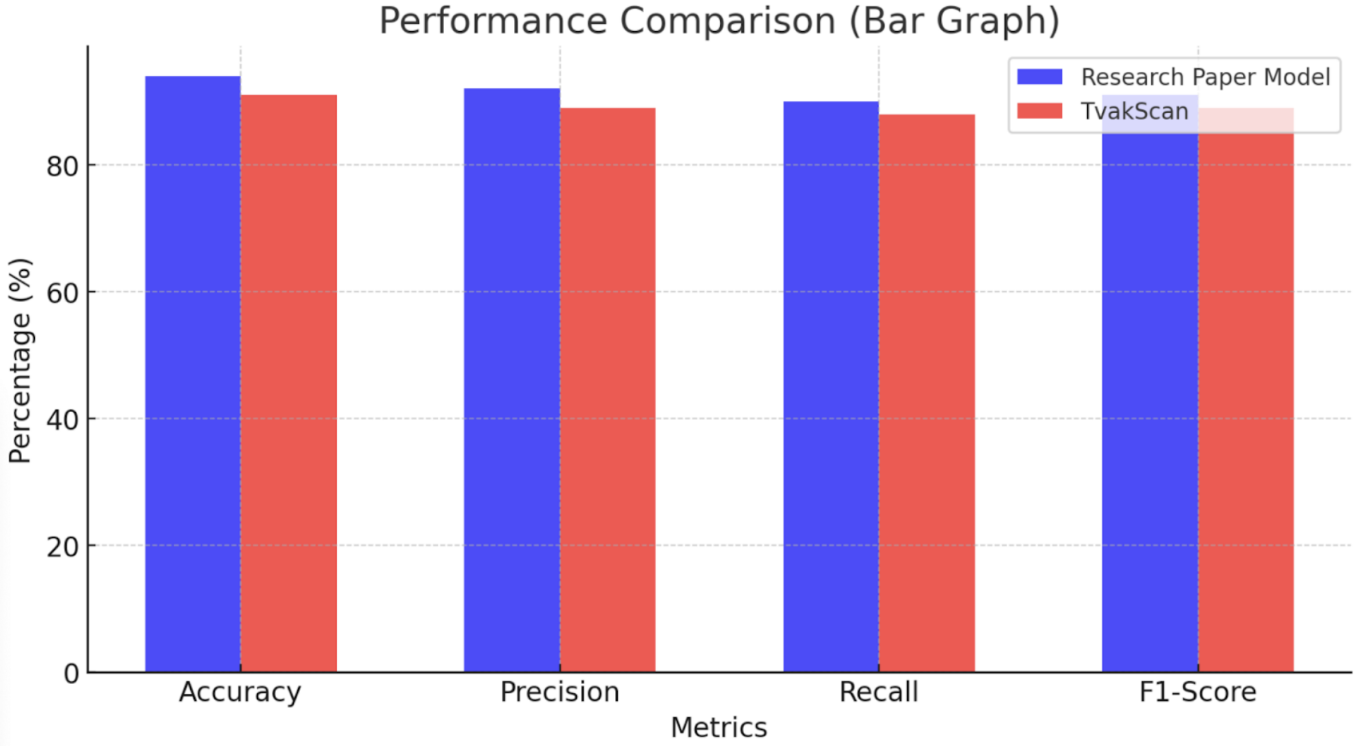

Fig. 4. Performance Comparison (Bar Graph)

The bar chart further visualizes TvakScan’s efficiency in classification tasks, confirming its ability to provide accurate, interpretable, and fast predictions for users and dermatologists. The system's robust precision (89%) and recall (88%) emphasize its reliability in identifying affected skin regions while minimizing false positives. These results reinforce TvakScan’s practical usability, diagnostic support, and real-time processing capabilities, making it a valuable tool for dermatological analysis and early detection.

VII. CONCLUSION

TvakScan effectively identifies skin anomalies with high accuracy, aiding early detection and diagnosis. Its AI-powered analysis, intuitive interface, and visual reports enhance dermatological assessments. By providing quick and reliable insights, TvakScan empowers users and healthcare professionals, improving skin health awareness and facilitating timely medical intervention for better patient outcomes.

VIII. FUTURE SCOPE

TvakScan has the potential to revolutionize dermatological diagnostics through advancements in AI and deep learning. Future enhancements could include expanding the dataset to improve accuracy across diverse skin tones and rare conditions. Integration with telemedicine platforms can enable remote consultations, making dermatological care more accessible. Implementing real-time skin health monitoring and personalized skincare recommendations using AI can enhance user engagement. Additionally, incorporating blockchain for secure medical record storage can ensure privacy and data integrity. Future iterations may also include wearable compatibility for continuous skin health tracking. By leveraging cutting-edge technologies and expanding its capabilities, TvakScan can significantly contribute to early disease detection, preventive healthcare, and global dermatology advancements, ultimately improving patient outcomes and healthcare accessibility worldwide.

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