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# Advance Deep learning for malnutrition assessment

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***ABSTRACT***

*Malnutrition remains a critical global health challenge, with profound implications for both physical and cognitive development across various populations. Its effects are particularly severe in vulnerable groups, including children, who are at a crucial stage ofgrowth and development, and the elderly, who may face increased nutritional needs due to age-related health conditions. The World Health Organization highlights that malnutrition, whether in the form of undernutrition, micronutrient deficiencies, or obesity,contributes to a range of health issues, including stunted growth, weakened immune systems, and increased mortality rates.*

*In light of this pressing issue, this project aims to leverage advanced deep learning techniques to enhance the assessment and identification of malnutrition indicators across diverse demographics. By employing a multi-faceted approach that integrates both computer vision and natural language processing, we propose a comprehensive framework that effectively analyzes dietary patterns, anthropometric data (such as height, weight, and body mass index), and social determinants of health. This analysis will utilize a variety of data sources, including images of food items, textual dietary reports, and sensor data from wearable devices that track individual health metrics.*

*The methodology of this project includes the development of convolutional neural networks (CNNs) specifically designed for image analysis. These networks will focus onrecognizing food items and estimating portion sizes, which are critical for accurately assessing dietary intake. In parallel, we will implement recurrent neural networks (RNNs) to process self-reported dietary intake data, allowing for a more comprehensive understanding of an individual's nutritional habits over time. This dual approach ensuresthat both visual and textual data are utilized to provide a more holistic view of nutritional status.*

*Moreover, this project will explore the use of transfer learning, a technique that allows models trained on large datasets to be adapted to smaller, domain-specific datasets. This is particularly relevant in malnutrition research, where collecting extensive labeled data can be challenging. By enhancing model accuracy in situations with limited data, we aim to improve the reliability of our assessments and predictions.*

*Our anticipated outcomes include the creation of a robust and scalable tool tailored for health professionals. This tool will facilitate real-time assessments of nutritional status and enable the identification of at-risk individuals, allowing for timely interventions. By integrating these advanced technologies, we aim to improve public health strategiesand interventions, ultimately contributing to better nutrition and health outcomes on a*

ISSN 2347–3657
Volume 12, Issue 4, 2024

*global scale. This project seeks not only to address immediate malnutrition issues but also to promote long-term health and well-being in populations at risk.*

## INTRODUCTION

The Malnutrition Detection System, leveraging the capabilities of Efficient Net and built on Python's Django framework with SQLite, marks a significant advancement in health technology. This deep learning project is meticulously designed with distinct modules for users, administrators, and doctors, each catering to specific functionalities and user experiences.

**User Module**: Users can sign up and log in to access a sophisticated malnutrition detection tool. They input critical data like gender, age, weight, height, and upload images of nails or skin. The system, powered by Efficient Net, analyzes these inputs to predict malnutrition, classifying results as either 'normal' or 'malnourished.

Post-prediction, users are recommended to local doctors for further consultation if needed. They can also view their prediction history, with details on result accuracy and health status of the submitted images.

**Admin Module**: The admin module provides a secure login for administrators who can access a comprehensive dashboard. This includes an overview of user counts, prediction results, and registered doctors. Admins can view all user prediction histories, manage registered user, and doctor profiles, and maintain system security by changing passwords

**Doctor Module:** Doctors have a dedicated signup and login facility. They can view the prediction histories of patients from their city, facilitating informed medical interventions. This module also allows doctors to manage their profiles and credentials, ensuring an efficient and secure system interaction.

In essence, this Malnutrition Detection System stands as a beacon of innovation in healthcare, providing a crucial tool for early diagnosis and intervention in malnutrition cases, thus paving the way for a healthier society.

## LITERATURE SURVEY

Malnutrition is a multifaceted global health challenge that affects millions of individuals across various demographics, including children, adolescents, adults, and the elderly. It encompasses both undernutrition—characterized by deficiencies in essential nutrients, calories, and vitamins—and overnutrition, which often results in obesity and related non-communicable diseases. The consequences of malnutrition extend far beyond immediate health concerns; they significantly impact physical and cognitive development, leading to long-term repercussions for individuals and societies.

In children, undernutrition can hinder growth, impair cognitive function, and increase vulnerability to infectious diseases. These early-life nutritional deficits can set off a cascade of adverse outcomes, limiting educational achievements and economic productivity later in life. Conversely, overnutrition, prevalent in many industrialized nations, contributes to a surge in obesity rates, diabetes, cardiovascular diseases, and other health complications. Elderly populations are particularly susceptible to malnutrition, whether due to inadequate intake, absorption issues, or metabolic changes, which can lead to increased

ISSN 2347–3657
Volume 12, Issue 4, 2024

morbidity, frailty, and a decline in quality of life.

Addressing malnutrition is crucial for achieving global health targets, such as thoseoutlined in the United Nations Sustainable Development Goals. Effective intervention requires accurate assessment and monitoring of nutritional status, which has traditionally relied on labor-intensive methods and subjective evaluations. However, recent advancements in deep learning techniques and artificial intelligence are revolutionizing this field, enabling healthcare professionalsto leverage large datasets for more precise assessments. These technologies facilitate the identification of at-risk populations and support timely, evidence-based interventions tailored to individual needs.

By harnessing the power of deep learning, we can not only enhance our understanding of malnutrition patterns but also improve public health strategies, ultimately leading to better health outcomes across vulnerable populations. The integration of these advanced methodologies into nutritional monitoring and intervention frameworks represents a significant step forward in the fight againstmalnutrition on a global scale

## HARDWARE AND SOFTWARE REQUIREMENT

In this chapter we mentioned the software and hardware requirements, which are necessary for successfully running this system. The major element in building systems is selecting compatible hardware and software. The system analyst has todetermine what software package is best for the "Malnutrition Detection System" and, where software is not an issue, the kind of hardware and peripherals needed for the final conversion

*System Environment:*

After analysis, some resources are required to convert the abstract system into thereal one.

The hardware and software selection begins with requirement analysis, followed bya request for proposal and vendor evaluation.

Software and real system are identified. According to the provided functional specification all the technologies and its capacities are identified. Basic functions and procedures and methodologies are prepared to implement. Some of the Basicrequirements such as hardware and software are described as follows: -

*Hardware and Software Specification*

- Software Requirements:
- Technology: Python Django
- IDE: Pycharm/VSCode
- Client-Side Technologies: HTML, CSS, JavaScript, Bootstrap
- Server-Side Technologies: Python
- Data Base Server: Sqlite

ISSN 2347–3657
Volume 12, Issue 4, 2024

- Operating System: Microsoft Windows/Linux

*Hardware Requirements:*

- Processor: Pentium-III (or) Higher
- Ram: 64MB (or) Higher
- Hard disk: 80GB (or) Higher

## SYSTEM ANALYSIS

The purpose of the Malnutrition Detection System using Efficient Net is to providean innovative and user-friendly platform for early detection and management of malnutrition. This project aims to harness the power of deep learning and image analysis to assess nutritional health based on user-provided data and images. By enabling users to quickly identify signs of malnutrition, the system seeks to facilitate timely medical intervention and connect them with local healthcare providers for further assistance. Additionally, it serves as a valuable resource for awareness and education about malnutrition, empowering users with knowledge about their health status. For healthcare professionals, it offers a comprehensive overview of patient health trends in their area, aiding in effective and targeted medical care. This project is a step towards bridging the gap between advanced healthcare technologies and everyday health management, especially in communities where access to healthcare is limited

## IMPLEMENTATION ISSUES

**HTML-**

HTML (Hypertext Markup Language) is the standard markup language usedto create web pages. It is a structured language that allows developers to define the structure of content on a webpage using tags, attributes, and elements. HTML provides a way for web browsers to interpret and display content in a structured and organized manner.

**CSS-**

CSS (Cascading Style Sheets) is a style sheet language used for 'describing the presentation of a document written in HTML. It enables developers to separate the structure of a webpage from its presentation. CSS allows developers to define the visual appearance of a webpage, such as font styles, colors, and layout.

**JavaScript-**

JavaScript is a high-level, interpreted programming language used to createinteractive web pages. It is a client-side scripting language that allows developers to add dynamic elements and behavior to web pages. JavaScriptcan manipulate HTML and CSS in real-time, making web pages more responsive and engaging.

**Bootstrap-**

Bootstrap is a free and open-source CSS framework that is widely used to create responsive and mobile-first web pages. It provides pre-built CSS styles and JavaScript plugins that developers can use to create professional-looking web pages quickly and easily. Bootstrap is compatiblewith all modern web

ISSN 2347–3657
Volume 12, Issue 4, 2024

browsers and devices.

**Python -**

Python is a high-level, general-purpose programming language used tocreate a wide range of applications. It is a popular language for web
development, scientific computing, data analysis, artificial intelligence, andmany other areas. Python is known for its simplicity, readability, and easy-to-learn syntax.

**Django -**

Django is a free and open-source web framework written in Python. It followsthe model-view. controller (MVC) architectural pattern and is designed to help developers build web applications quickly and easily. Django provides a number of built-in features, such as an object-relational mapper 1 (ORM), automatic admin interface, and URL, routing, that simplify web application development

**Sqlite.**

SQLite is a lightweight, serverless, and self-contained relational database management system. It is widely used in web applications and mobile apps,as it requires minimal configuration and administration. SQLite is compatiblewith all major programming languages and provides a simple and efficient way to store and retrieve data.

**Efficient Net**

Efficient Net is a highly efficient deep learning architecture designed for computer vision tasks, including medical image analysis. It optimizes both accuracy and computational efficiency by scaling the model's depth, width, and resolution. In the context of a lung cancer prediction system, Efficient Net can analyze medical images such as chest X-rays or CT scans to accurately predict cancerous or non-cancerous conditions. Its efficiency andeffectiveness contribute to improved diagnostic accuracy and potentially earlier detection of lung cancer

## SYSTEM DESIGN

### 1.1 Use Case Diagram:

* Use case diagram consists of use cases and actors and shows theinteraction between them.
The key points are:

* The main purpose is to show the interaction between the use cases and theactor.
* To represent the system requirement from the user's perspective.
* The use cases are the functions that are to be performed in the module.

International Journal of
Information Technology & Computer Engineering
ISSN 2347–3657
Volume 12, Issue 4, 2024

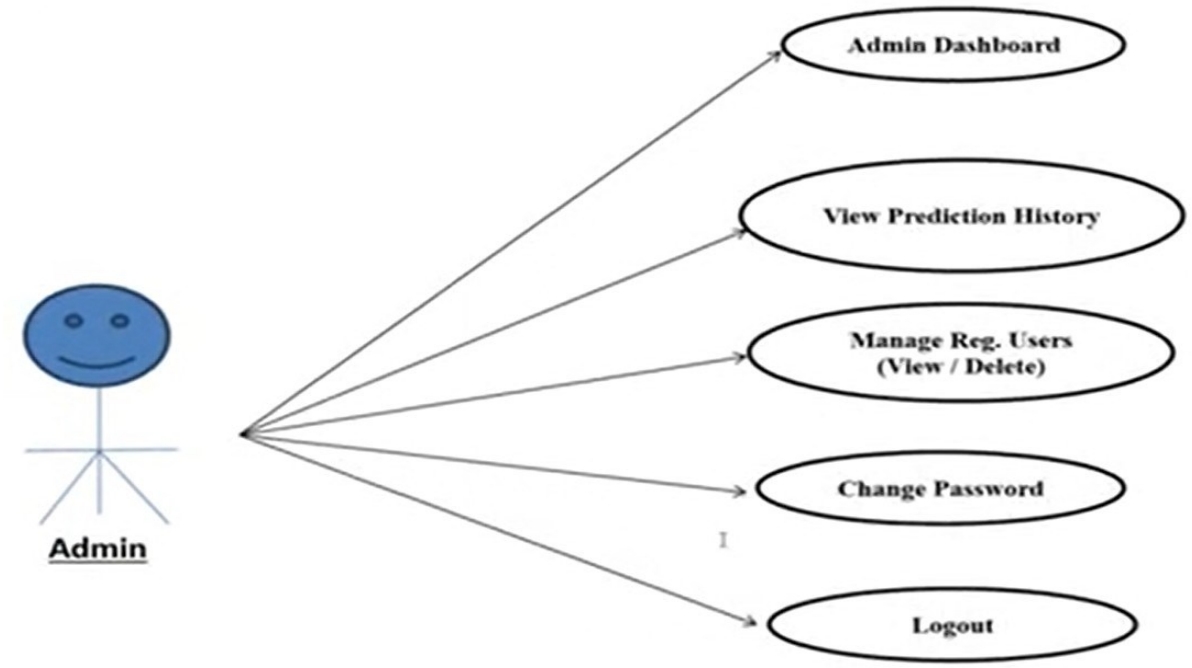



Fig 6.1 use case diagram- admin

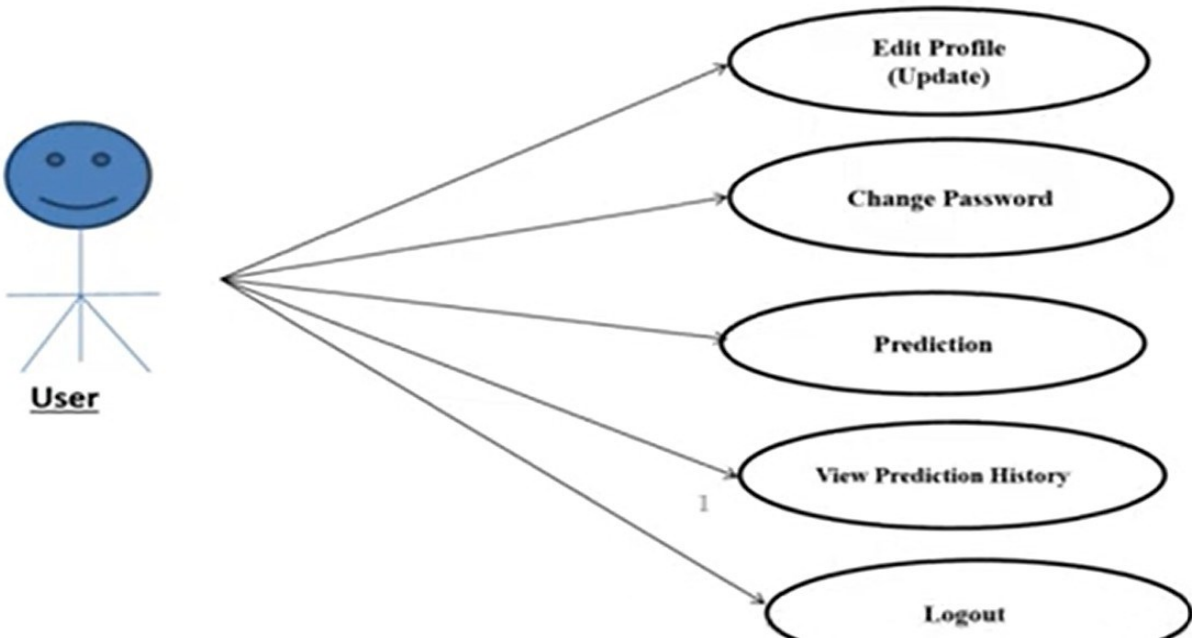
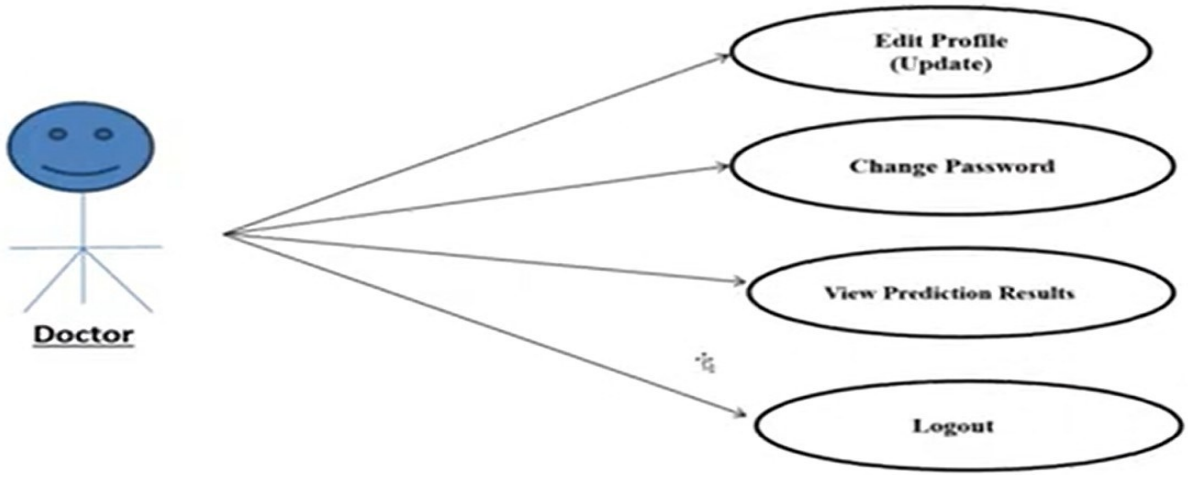
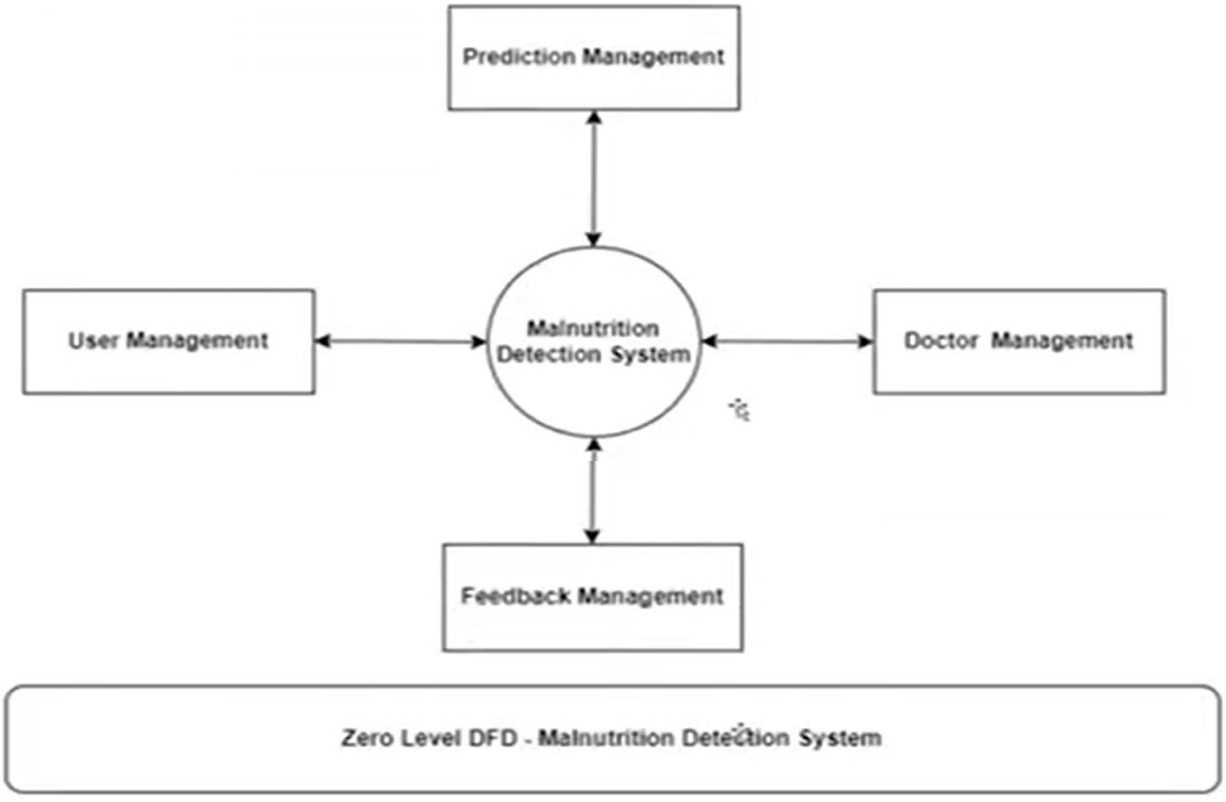



Fig 6.2 use case diagram -user

International Journal of
Information Technology & Computer Engineering
ISSN 2347–3657
Volume 12, Issue 4, 2024




## 1.2 Data Flow Diagram(DFD)DFD




**level 0 :**

**Fig 6.4 DFD level 0**

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 12, Issue 4, 2024

Fig 6.5 DFD level 1

## 1.3 ER diagram

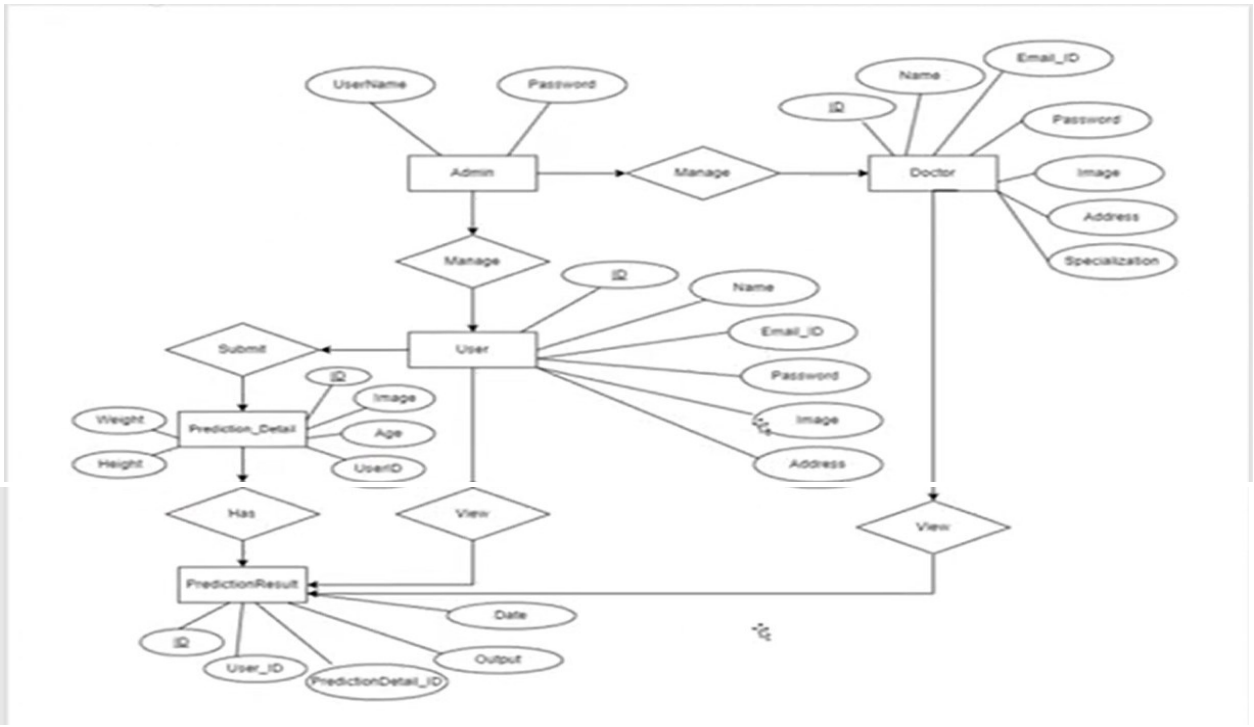



Fig 6.6 ER diagram

## 1.4 Sequence Diagram

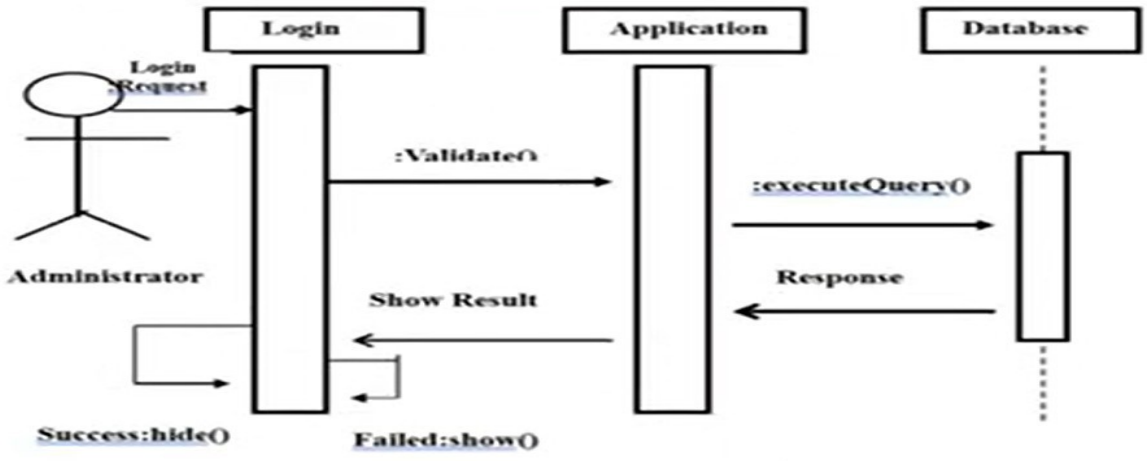



Fig 6.7 Sequence Diagram For Administrator

ISSN 2347–3657
Volume 12, Issue 4, 2024

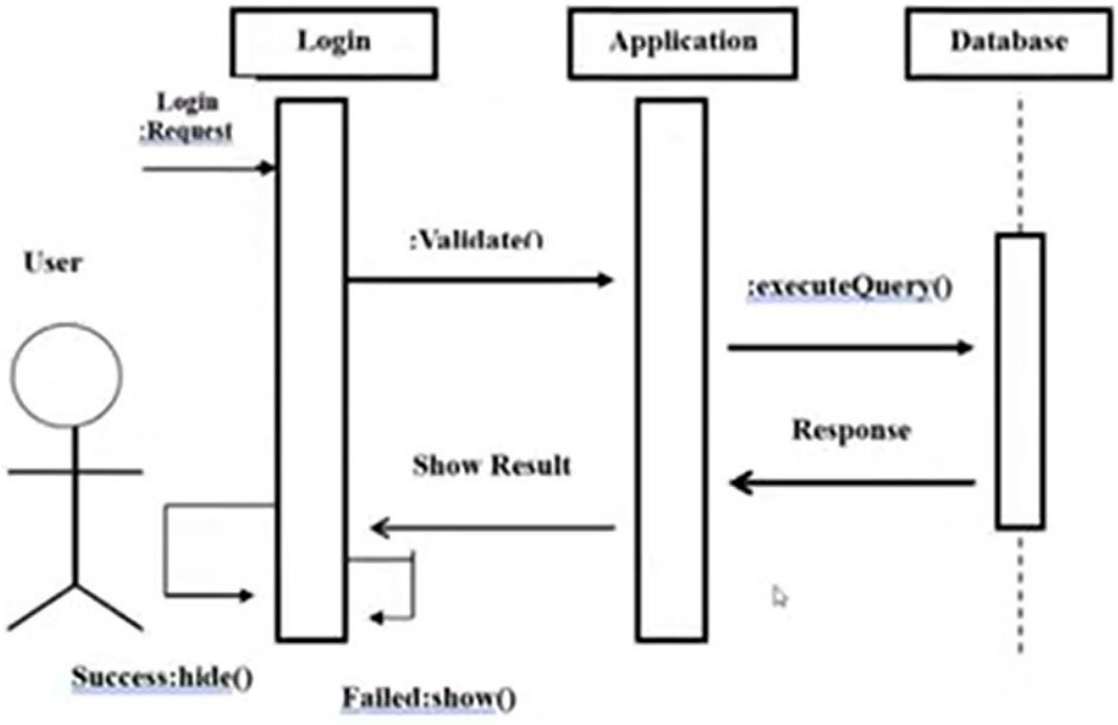



**Fig 5.8 Sequence Diagram for user**

```
# CODINGImport necessary libraries
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
Dropout, GlobalAveragePooling2D
from tensorflow.keras.preprocessing.image import ImageDataGenerator from
tensorflow.keras.callbacks import EarlyStopping, ModelCheckpointfrom sklearn.metrics import
classification_report, confusion_matrix import cv2
import os
import matplotlib.pyplot as plt
from keras_tuner import RandomSearch

# 1. Data Preprocessing and Normalization
def preprocess_images(image_dir, target_size=(128, 128)): processed_images = []
    labels = []
```

ISSN 2347–3657
Volume 12, Issue 4, 2024

```
    for class_dir in os.listdir(image_dir):
        class_path = os.path.join(image_dir, class_dir)if
        os.path.isdir(class_path):
            for img_name in os.listdir(class_path):
                img_path = os.path.join(class_path, img_name)img =
                cv2.imread(img_path)
                img = cv2.resize(img, target_size)
                img = img / 255.0          # Normalizing the pixel values
                processed_images.append(img) labels.append(class_dir)

    return np.array(processed_images), np.array(labels)

# Example usage
data_dir = "/path/to/data"          # Replace with the path to your dataset train_images,
train_labels = preprocess_images(f"{data_dir}/train")
val_images, val_labels = preprocess_images(f"{data_dir}/validation")

# Image Data Generators for real-time data augmentation
train_datagen = ImageDataGenerator(rescale=1.0/255, rotation_range=15,width_shift_range=0.1,
height_shift_range=0.1, zoom_range=0.2, horizontal_flip=True)
val_datagen = ImageDataGenerator(rescale=1.0/255)

train_generator = train_datagen.flow_from_directory( directory=f"{data_dir}/train",
    target_size=(128, 128),
    batch_size=32,
    class_mode="binary"
)

val_generator = val_datagen.flow_from_directory(
    directory=f"{data_dir}/validation", target_size=(128, 128),
    batch_size=32,
    class_mode="binary"
)

# 2. Model Architecture with Transfer Learning
base_model = tf.keras.applications.ResNet50(weights='imagenet', include_top=False, input_shape=(128, 128, 3))
for layer in base_model.layers:
```

ISSN 2347–3657
Volume 12, Issue 4, 2024

```
    layer.trainable = False

model = Sequential([ base_model,
    GlobalAveragePooling2D(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam', loss='binary_crossentropy',metrics=['accuracy'])

# Callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=5,restore_best_weights=True)
model_checkpoint = ModelCheckpoint("best_model.h5", save_best_only=True)

# Training the Modelhistory
=model.fit(
    train_generator,
    epochs=30,
    validation_data=val_generator, callbacks=[early_stopping,
    model_checkpoint]
)

# 3. Hyperparameter Tuning with Keras Tunerdef
build_model(hp):
    model = Sequential()
    model.add(Conv2D(hp.Int('conv_units', min_value=32, max_value=128, step=32),
                (3, 3), activation='relu', input_shape=(128, 128, 3)))
    model.add(MaxPooling2D(2, 2))model.add(Flatten())
    model.add(Dense(hp.Int('dense_units', min_value=64, max_value=256,step=64), activation='relu'))
    model.add(Dropout(0.5)) model.add(Dense(1,
    activation='sigmoid'))

    model.compile( optimizer=tf.keras.optimizers.Adam(hp.Choice('learning_rate', [1e-2, 1e-3,
1e-4])),
        loss='binary_crossentropy',
        metrics=['accuracy']
```

ISSN 2347–3657
Volume 12, Issue 4, 2024

```
    )
    return model

# Hyperparameter searchtuner=
RandomSearch(
    build_model, objective='val_accuracy',
    max_trials=5, executions_per_trial=1,
    directory='hyperparam_search',
    project_name='malnutrition_assessment'
)

tuner.search(train_generator, epochs=10, validation_data=val_generator) best_model=
tuner.get_best_models(num_models=1)[0]

# 4. Evaluation
val_loss, val_accuracy = model.evaluate(val_generator)
print(f"Validation Loss: {val_loss:.4f}, Validation Accuracy: {val_accuracy:.4f}")

y_true = val_generator.classes
y_pred = (model.predict(val_generator) > 0.5).astype("int32") print(classification_report(y_true, y_pred))
cm = confusion_matrix(y_true, y_pred)print("Confusion Matrix:\n",
cm)

# 5. Visualization of Training and Validation Performancedef
plot_training_history(history):
    plt.figure(figsize=(12, 4))
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Train Accuracy')
    plt.plot(history.history['val_accuracy'], label='Val Accuracy')plt.title('Model
    Accuracy')
    plt.xlabel('Epochs')
```

**TESTING**

Testing of the Malnutrition Detection System is crucial to ensure its reliability, accuracy, and user-friendliness. The testing process can be categorized into different types, each addressing specific aspects of the system:

1. Unit Testing: Involves testing individual components or units of the systemto ensure each part

ISSN 2347–3657
Volume 12, Issue 4, 2024

functions correctly in isolation. This includes testing individual functions. methods, classes, or modules, especially the algorithmsused formalnutrition prediction.

2. Integration Testing: Focuses on testing the interaction between different modules of the system. For instance, how the user module interacts with theprediction module or how the admin module retrieves data from the database.

3. System Testing: Encompasses testing the complete and integrated software to evaluate its compliance with specified requirements. This includes checking the entire application for bugs, glitches, and other issues

4. Usability Testing: This form of testing is user-centric and aims to ascertainhow user- friendly the application is. It involves subjects from the intended audience using the system to identify navigational difficulties, user interfaceissues, and overall user experience.

5. Performance Testing: Tests the system's performance under various conditions, including its response time, reliability, and resource usage. This is particularly important for ensuring the system's prediction algorithms perform well under different load conditions.

6. Security Testing: Involves testing the system for vulnerabilities that could potentially be exploited. This is crucial given the sensitive nature of user data,especially medical information

7. Compatibility Testing: Ensures the system works seamlessly across different devices, browsers, and operating systems, providing a consistentuser experience.

8. Regression Testing: Conducted after any changes or updates to thesoftware, ensuring that new code changes do not adversely affect theexisting functionality of the system.

9. Acceptance Testing: The final phase of testing, often performed by the end-users, to validate the end-to-end business flow. It works as a verifier toensure the system meets the business requirements and is ready for deployment

## ADVANTAGES AND LIMITATION

**Advantages of "Malnutrition Detection System":**

The Malnutrition Detection System, leveraging Efficient Net and developedwith Python

Django and SQLite, present numerous advantages, making it a significantcontribution to healthcare technology.

Some of the key benefits include:

1. Early Detection of Malnutrition: By analyzing user-provided data and images, the system can

ISSN 2347–3657
Volume 12, Issue 4, 2024

identify signs of malnutrition early, enabling timelyintervention andtreatment.

2. Increased Accessibility: The online platform allows users from remote locations to access malnutrition detection services without needing to visithealthcare facilities in person.

User-Friendly Interface: Designed with simplicity in mind, the system is accessible to users of all ages and technical proficiencies, ensuring a broaduser base.

3. Cost-Effective Solution: It provides a cost-effective alternative totraditional medical consultations, which can be expensive and
time-consuming.

4. Enhanced Accuracy: Utilizing Efficient Net, a state-of-the-art deep learningmodel, enhances the accuracy of malnutrition detection compared to traditional methods.

5. Data-Driven Recommendations: The system not only detects malnutritionbut also recommends local doctors, facilitating effective follow-up treatment.

6. Privacy and Security: User data is securely managed, ensuringconfidentiality and privacy of sensitive health information.

These advantages make the Malnutrition Detection System a valuable assetin the healthcare sector, particularly in areas where access to medical services is limited. It stands as a testament to how technology can be harnessed to address critical health issues effectively.

**Limitations of "Malnutrition Detection System":**

The Malnutrition Detection System, while innovative and beneficial, also hascertain limitations that need to be considered. Some of these include:

1. Dependency on User-Provided Data: The accuracy of the predictions heavily relies on the quality and reliability of the data and images provided byusers. Inaccurate or low-quality submissions can lead to incorrect assessments.

2. Limited Scope of Diagnosis: The system focuses on malnutrition detectionand may not identify other nderlying health conditions that might be present.

Technology Accessibility: Users without access to necessary technologyor internet connectivity might not be able to utilize the system effectively.

3. Lack of In-Person Assessment: While the system provides preliminary assessments, it cannot

ISSN 2347–3657
Volume 12, Issue 4, 2024

replace the comprehensive diagnosis that comes from in-person medical consultations.

4. Data Privacy Concerns: Despite security measures, the collection and storage of personal health data always carry a risk of privacy breaches and data misuse

5. Potential for Misinterpretation: Users might misinterpret the results without proper medical guidance, leading to unnecessary anxiety or neglect of serious health issues.

6. Software and Hardware Limitations: The system's performance is dependent on the software and hardware used, which might limit its functionality or accuracy.

7. Cultural and Language Barriers: The system might not be accessible or user friendly for non-English speakers or those from different cultural backgrounds.

8. Lack of Holistic Health Analysis: The system does not consider the full medical history or lifestyle factors of users, which can be crucial in understanding and treating malnutrition.

9. Over-reliance on Technology: There is a risk that users or even healthcare providers might over-rely on the system's predictions, overshadowing traditional and potentially more reliable medical practices.

Understanding these limitations is crucial for the continued development and improvement of the Malnutrition Detection System, ensuring it becomes a more effective and reliable tool in healthcare..

## CONCLUSION AND FUTURE SCOPE

### FUTURE SCOPE

The Malnutrition Detection System, harnessing the power of Efficient Net and Django, holds significant potential for future development and enhancement. Its future scope includes:

1. Advanced Image Analysis: Integrating more sophisticated image processing techniques to improve accuracy in detecting malnutrition from skin and nail images.

2. Expansion of Detection Capabilities: Broadening the system's capabilities to identify other nutrition-related disorders or health conditions.

3. Integration with Healthcare Systems: Linking the system with existing healthcare databases and records for a more comprehensive assessment of a patient's health.

4. Mobile Application Development: Creating a mobile app version of the system to increase accessibility and ease of use for users across different devices

5. Real-Time Data Analysis: Implementing real-time analytics for immediate feedback and guidance to users upon uploading their images and data.

6. Enhanced Al Algorithms: Continuously updating and refining the machine learning models to improve prediction accuracy and efficiency.

7. Global Language Support: Making the system multilingual to cater to a diverse global user base,

ISSN 2347–3657
Volume 12, Issue 4, 2024

breaking language barriers in healthcare access.

8. User Education and Awareness: Integrating educational resources about malnutrition, its symptoms, and prevention methods to increase user awareness and self-care.

9. Collaboration with Medical Professionals: Partnering with doctors and healthcare professionals to validate predictions and provide expert insights.

10. Wearable Device Integration: Exploring possibilities to link the system with wearable health devices for continuous monitoring of health indicators relevant to nutrition.

11. Community and Social Features: Adding community-driven features where users can share experiences, tips, and support each other in managing health.

12. Telemedicine Integration: Facilitating virtual consultations with healthcare professionals based on the system's predictions, bridging the gap between preliminary assessment and professional medical advice.

13. Research and Development: Using data collected from the system for research purposes to better understand malnutrition trends and effectiveness of various interventions.

By addressing these areas, the Malnutrition Detection System can evolve into a more holistic, user-friendly, and medically comprehensive tool, contributing significantly to public health and individual wellnest

## CONCLUSION

The Malnutrition Detection System, developed using EfficientNet and Django, represents a significant advancement in the intersection of technology and healthcare. This innovative system is designed to enhance public health initiatives, particularly in the detection and management of malnutrition, which remains a pressing global health concern. By employing deep learning algorithms, the system provides a practical and accessible solution for early detection of malnutrition based on visual indicators observed in skin and nail images.

One of the standout features of this system is its user-friendly interface, which makes it easy for individuals, regardless of their technical expertise, to conduct preliminary health assessments. Users can upload images and receive immediate feedback on potential nutritional deficiencies, thereby enabling timely interventions. This accessibility is crucial, especially in underserved regions where healthcare resources may be limited.

In addition to serving individual users, the system facilitates a seamless connection between patients and healthcare providers. By leveraging location-based services, it helps match users with local healthcare professionals for further consultation and treatment. This not only streamlines the process of seeking medical advice but also fosters a collaborative environment

ISSN 2347–3657
Volume 12, Issue 4, 2024

where patients can receive personalized care tailored to their specific needs.

For healthcare administrators, the Malnutrition Detection System provides a comprehensive overview of user activities, predictive analytics, and health trends. By analyzing aggregated data, administrators can identify patterns in malnutrition prevalence and monitor the effectiveness of interventions over time. This insight assists in informed decision-making processes, allowing public health officials to allocate resources more effectively and implement targeted programs to combat malnutrition.

Furthermore, the integration of advanced machine learning techniques with healthcare underscores the transformative potential of artificial intelligence in improving health outcomes. The Malnutrition Detection System not only aids in the early identification of malnutrition but also lays the groundwork for more informed and proactive health management strategies.

In conclusion, this project exemplifies the vital role of technological innovation in addressing critical health issues. By bridging the gap between technology and healthcare, the Malnutrition Detection System enhances the efficiency of medical diagnosis and patient care. As we look to the future, this system sets a precedent for ongoing advancements in the field, highlighting the importance of continued investment in digital health solutions to improve global health outcomes. Through initiatives like this, we can foster a healthier, more informed population, better equipped to tackle the challenges of malnutrition and beyond.

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ISSN 2347–3657
Volume 12, Issue 4, 2024

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