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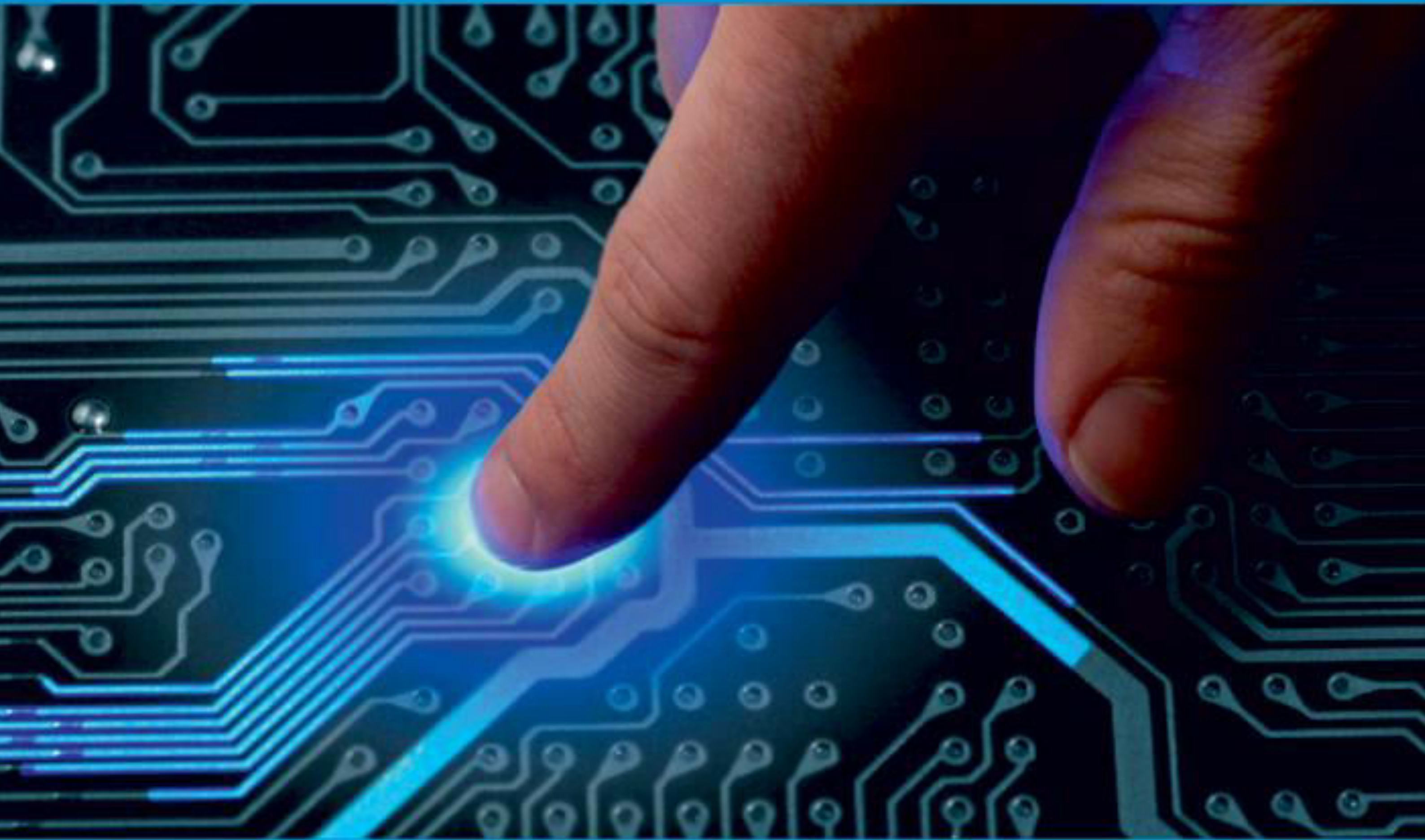

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International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

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Noral: AI Driven Oral Healthcare Appointment System

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ABSTRACT: This paper proposes a revolutionary approach to dental healthcare, eliminating the need for traditional preliminary screenings and instead utilizing an AI-based solution. By using Natural Language Processing (NLP), patients can describe their symptoms in everyday language and receive immediate advice and insights. Additionally, Convolutional Neural Networks (CNN) are utilized to analyze images of dental conditions, providing an evidence-based method for identifying oral health issues. The platform also includes a robust business logic layer for efficient appointment scheduling, benefiting both patients and dentists. Through the combination of intelligent automation and user-friendly design, this solution aims to increase access, reduce wait times, and improve overall efficiency in dental healthcare systems.

KEYWORDS: Dental Healthcare, Convolutional Network, Natural Language Processing, API of deep learning models, Web Application.

I. INTRODUCTION

In the world of traditional healthcare, patients often have to rely on intermediaries or systems that use subjective judgment when recording symptoms and assessing concerns before scheduling dentist appointments. This outdated approach can result in inefficiencies such as miscommunication, human error, and delays. Current digital solutions lack advanced technologies like Convolutional Neural Networks (CNNs) and Natural Language Processing (NLP), limiting both accuracy and user experience. To address these issues, we propose a state-of-the-art prototype that leverages AI to streamline dental healthcare processes, eliminating intermediaries while enhancing efficiency and precision. The core of this system is a CNN-based pipeline that accurately analyses dental images. Our primary diagnostic model achieves an impressive 97% accuracy in detecting dental issues, while our auxiliary model has a 96% accuracy rate in verifying if the input image shows teeth. This ensures that only relevant inputs are processed, reducing errors and increasing reliability. Through the use of CNN-based ensembling techniques with hard voting, predictions from multiple models are combined to refine outputs and further improve accuracy. In addition, NLP capabilities interpret patient-provided symptom descriptions, providing initial advice and guiding diagnostics.

Our prototype, developed with Streamlit, offers a lightweight and efficient interface to showcase its AI capabilities. Designed as an API-based solution, it seamlessly integrates into existing systems or third-party applications. By focusing on AI-powered image analysis, symptom interpretation, and appointment management, our adaptable solution addresses critical inefficiencies. Unlike traditional methods or outdated systems, our AI-driven prototype eliminates subjectivity, enhances accuracy, and minimizes delays. By combining advanced CNN and NLP technologies with streamlined appointment management, it has the potential to revolutionize dental healthcare by making it more accessible, efficient, and patient-centred.

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II. LITERATURE REVIEW

The advancement of AI and deep learning has greatly enhanced diagnostic capabilities in various medical and computational fields. In the detection of Oral Squamous Cell Carcinoma (OSCC), a comprehensive multimodal deep learning process that incorporates patient data and images increased accuracy, with MobileNetV3-Large achieving 81% in accuracy, precision, recall, and an F1-score of 78%. Another study by K.-C. Li et al. utilized YOLOv4 to identify tooth positions and AlexNet for recognizing symptoms on bitewing radiographs, leading to impressive accuracies of 92.85% for caries, 96.55% for restorations, and 91.13% for periodontal diseases. This demonstrates the potential for AI to improve precision and efficiency in dentistry. Furthermore, A.P. Sunilkumar et al. explored AI-driven methods for synthesizing panoramic X-rays (PXs) from CBCT scans and phantoms to overcome challenges such as limited datasets and privacy concerns, making PX imaging more accessible in the diagnostic process.

In another instance, A. Imak et al. presented a multi-input deep convolutional neural network ensemble (MI-DCNNE) that utilizes both raw and enhanced images to accurately detect dental caries at a rate of 99.13%. This showcases how AI can reduce diagnostic errors in dentistry. Outside of the healthcare realm, S. Kusal et al. provided an overview of advancements in conversational AI and emphasized incorporating emotions, sentiment analysis, and deep learning models to simulate human behaviour and enhance Human-Computer Interaction (HCI). They also identified areas for further research to continue improving HCI through conversational AI technology.

III. NORAL- AI DRIVEN ORAL HEALTHCARE PROPOSED SYSTEM

Our team's goal is to develop an AI-based solution for dental healthcare that will improve appointment management and the diagnosing process. This system will utilize Convolutional Neural Networks (CNNs) and Natural Language Processing (NLP) to automate tasks and increase accuracy. The use of both CNN and NLP allows for the analysis of visual and textual data, resulting in a more efficient workflow with fewer errors.

Overview of CNN and NLP:

- Convolutional Neural Networks (CNNs): These deep learning models are specifically designed for processing visual data. They can recognize features in images such as edges, textures, and patterns, allowing them to classify or detect objects. In our system, CNNs will analyze dental images to identify potential issues with teeth and oral health.
- Natural Language Processing (NLP): This technology enables computers to understand human language in its natural form. Through techniques like tokenization, semantic analysis, and text classification, NLP can interpret textual input. In our system, NLP will analyze patient descriptions of symptoms to provide initial advice and insights.

Synergy Between CNN and NLP:
By combining CNN and NLP, our system can utilize both image data and text descriptions to complement each other. While CNNs analyze visual symptoms from dental images, NLP can process the patient's verbal description of their issues. Together, they provide a comprehensive approach to diagnosis, reducing reliance on subjective human interpretation and improving accuracy.

Benefits of the Proposed System:
1. Accuracy: The use of advanced AI models reduces human error in diagnosis.
2. Efficiency: Automated processes for image and text analysis reduce the time needed for initial assessments.
3. Cost-Effectiveness: By eliminating the need for intermediary staff, costs can be reduced in the long run.
4. Scalability: Our system has the capability to handle a large number of patients without requiring additional human resources.
5. Convenience: Patients can access our system from anywhere, making it more convenient and accessible.

Disadvantages of Real-World Systems:
1. Human Errors: In traditional systems, intermediary staff may miss critical symptoms or make subjective errors in judgment.

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2. Missed Symptoms: Important details in patient complaints can be overlooked, resulting in incorrect assessments.
3. Time and Cost: Manual processes are slower and require more personnel, leading to higher operational costs.
4. Limited Efficiency: Existing systems lack the advanced diagnostic capabilities of CNNs and NLP, often only offering basic appointment scheduling without intelligent insights.

The Existing Systems Fall Short:
Current dental clinic management websites are not as efficient as they could be. They lack advanced technologies and rely on manual input or basic algorithms. Our system solves these challenges by harnessing the power of both CNN models and NLP models, streamlining workflows and improving patient experiences.

IV.NORAL- AI DRIVEN ORAL HEALTHCARE ARCHITECTURALE DIAGRAM

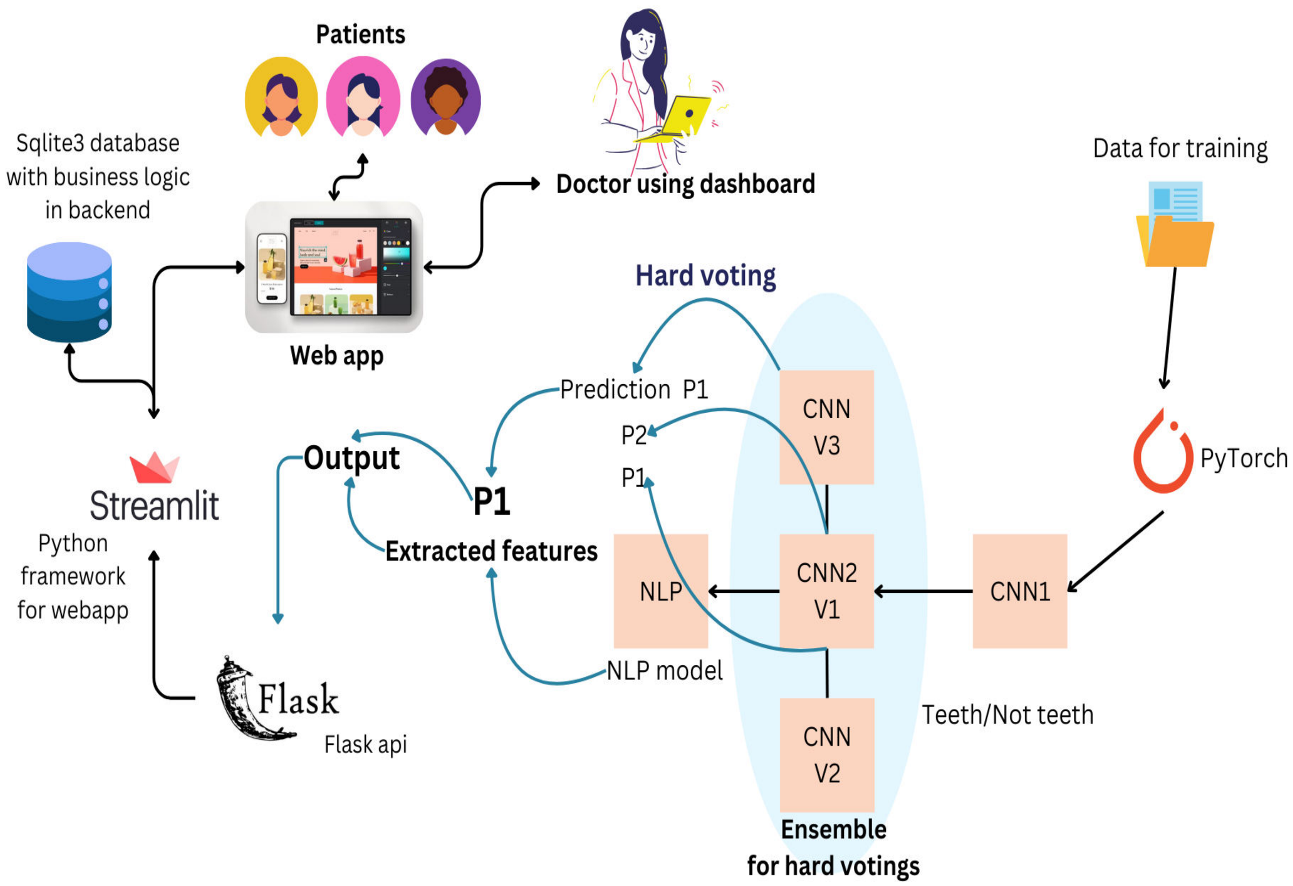

Figure-1: This is the entire architecture diagram of Noral

V. NORAL- AI DRIVEN ORAL HEALTHCARE METHODOLOGY

The development of this system required a thorough approach to gathering data, training models, designing the system, and optimizing it for accuracy, efficiency, and scalability. The methodology utilizes advanced AI techniques while also keeping practical implementation in mind for real-world dental healthcare processes. Image data for CNN models was obtained from sources such as Kaggle and other publicly available datasets. Limited augmentation was applied during preprocessing to maintain high-quality and realistic images. This decision aligns with the characteristics of pretrained models used in transfer learning, such as ResNet and VGG, which already undergo significant augmentation during their initial training. By utilizing the built-in augmentation of these models, we ensured compatibility with their learned

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feature representations while avoiding repetitive transformations. The CNN pipeline was then fine-tuned to meet the specific needs of dental image analysis.

In contrast, real-world data was not readily accessible for the NLP component. To overcome this limitation, synthetic data was generated using GPT 4-O Mini, a language model capable of producing highly realistic approximations. This artificial data closely mimicked natural patient inputs. While the NLP model trained on this data achieved perfect recall and precision scores during validation, it is acknowledged that these results may be inflated due to the controlled nature of the synthetic dataset. Further testing with real-world inputs is necessary to assess the model's true performance. Despite these challenges, the synthetic dataset played a crucial role in establishing the foundation for the NLP model's functionality. Ensembling techniques can be incorporated during deployment to further improve robustness and prevent overfitting. The CNN pipeline includes a dedicated model that verifies whether an uploaded image contains teeth or not, serving as an important filter to ensure only relevant inputs are processed. The primary diagnostic model then analyzes the images to identify specific dental issues, utilizing its pretrained capabilities and fine-tuned parameters for optimal performance. The NLP and CNN models work together to provide a comprehensive diagnostic assessment by combining their outputs. Patients can describe their symptoms in natural language, which the NLP model interprets, while the CNN models analyze any accompanying images, creating a cohesive diagnostic system.

To effectively manage patient data, the system integrates with a database. This serves as a repository for storing patient information and the combined results from both the NLP and CNN models. The stored data allows for automated appointment management through well-defined business logic, streamlining workflow and ensuring accurate and easily accessible records. Considering the high computational demands of deep learning models, optimization was a key consideration during system design. Heavy models, particularly those implemented using PyTorch, can cause latency issues. To address this, a Flask API was developed as the backend for prediction tasks. Separate prediction scripts for each model were integrated into the API, allowing for efficient communication with the frontend. By utilizing Flask's lightweight framework, predictions are handled smoothly, with data transferred over HTTP using POST and GET methods. This setup minimizes latency and ensures seamless integration between the models and user interface.

For the frontend of the application, Streamlit was used for its simplicity and quick development capabilities. It provides a user-friendly interface that allows patients to upload images, describe symptoms, and receive diagnostic results in an intuitive format. While not intended as a full end-to-end website, it serves as a functional prototype for showcasing the AI-powered appointment system and diagnostic solution. Overall, this methodology combines strong data handling practices, advanced model architectures, and practical optimizations to deliver an effective tool for revolutionizing dental healthcare. By integrating CNN and NLP models with a streamlined backend and user-friendly frontend, this system lays a solid foundation for future improvements and real-world deployment.

VI. IMPLEMENTATION MODULES OF NORAL- AI DRIVEN ORAL HEALTHCARE

The system was implemented with the goal of seamlessly integrating AI models, creating a user-friendly interface, and providing robust backend functionality. This involved designing and implementing various components, from the frontend interface to the backend model training and API integration.

6.1 Frontend Design:

Streamlit was used to develop the frontend of the application, offering an intuitive interface for users. The main page includes fields where patients can input personal information like name, age, and contact details - all required before accessing diagnostic results. These details are automatically stored in the database to ensure consistent record-keeping. A separate tab was created for doctor's dashboard, granting healthcare professionals access to patient records and allowing them to perform tasks such as viewing diagnostic results, organizing the database, and reviewing appointment requests. The system also incorporates business logic to automate repetitive tasks and streamline database management.

6.2 Backend and API Integration:

Flask was used to power the backend of the system, while Python's requests module facilitated communication between the frontend and trained models through the Flask API. This setup ensures secure and efficient data transfer over HTTP - for instance, when a user uploads an image or enters symptoms, this information is sent to the Flask API which processes it using CNN or NLP models and returns results to the frontend.

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6.3 Training CNN Models:

To train the CNN models, a structured dataset was used with separate folders for train and test splits, each with subfolders representing different dental issues or classifications. The torchscript library was utilized to create Dataset objects for training and testing, which were then passed into PyTorch's DataLoader to handle batching and shuffling of data during training. Pretrained models like EfficientNet and VGG were used as a starting point while transfer learning techniques were applied for fine-tuning on the dental image dataset. The training function computed loss and accuracy at each epoch, generating metrics that provided insights into model performance through visualization tools like Matplotlib. This allowed for monitoring of the training process and detection of potential issues like overfitting or underfitting. Detailed summaries of the models were also generated using the torchinfo library, providing information on architecture and parameters.

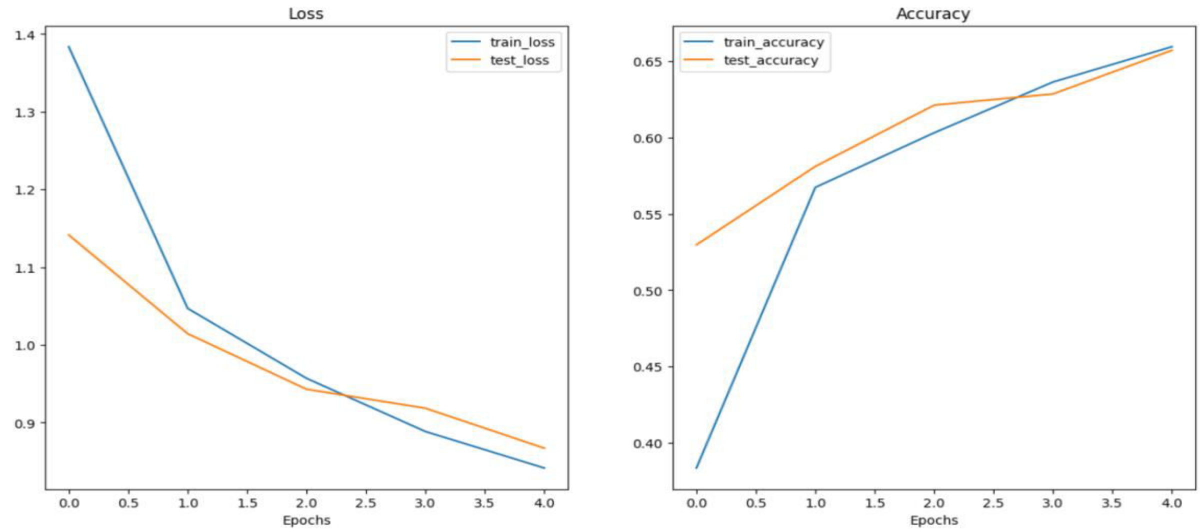

Figure-2: Loss and Accuracy curve of the model replicating Tiny-VGG architecture model to verify the teeth images

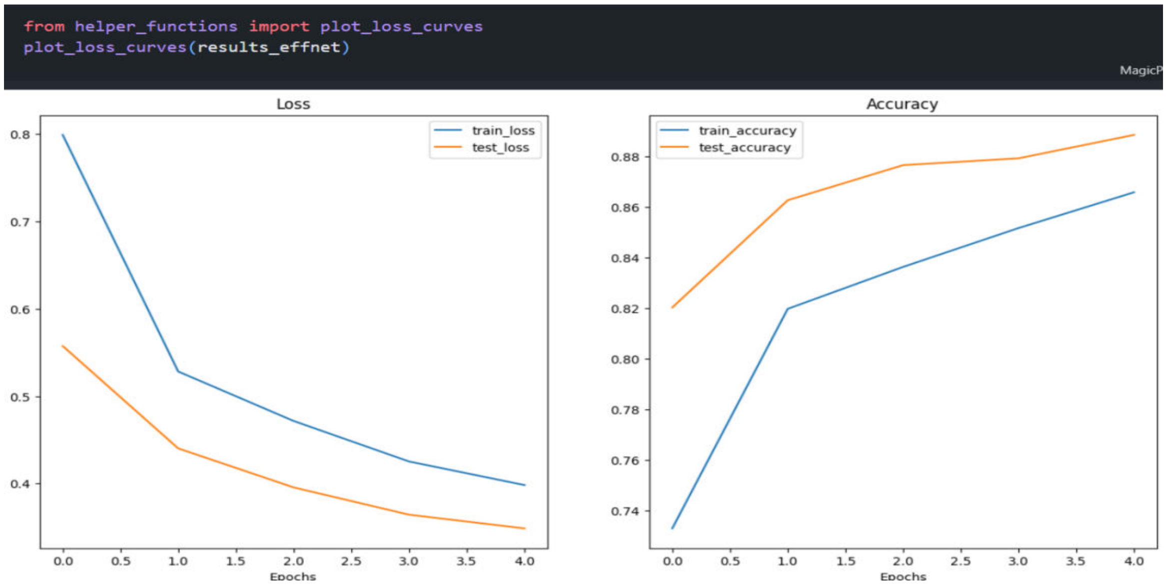

Figure-3: Loss and Accuracy curve of the EfficientNet model we trained on the oral-disease dataset

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6.4 Database Integration:
A sqlite3 database was connected to store patient information and appointment requests. This database also saved the cumulative results from both the NLP and CNN models, ensuring that all relevant data is available for review. The business logic in the doctor's dashboard allows for automated organization of this data, simplifying the workflow for healthcare professionals.

VII. NORAL- AI DRIVEN ORAL HEALTHCARE FUNCTIONALITIES

Our project consists of multiple functional modules, each with a specific role in efficiently managing dental healthcare workflows. These modules work together to create a comprehensive and user-friendly platform for automating dental processes. Here is an overview of each key module:

7.1. User Authentication Module: This module handles the login process for both patients and doctors separately. For patients, a dummy login system is in place for demonstration purposes only, while doctors have access to a basic interface for administrative tasks such as database management and appointment handling.

7. 2. Database Management Module: This module is responsible for storing and organizing patient information and appointments. Doctors can easily manage the database using intuitive dashboards, allowing them to update records or handle appointment schedules. Patient data and diagnostic results are automatically recorded during each interaction to ensure seamless data management.

7.3. AI Processing Module: This module incorporates advanced AI functions for comprehensive diagnostics, including. CNN Model: Used for analysing dental images to detect oral health issues and validate their authenticity. NLP Model: Processes text descriptions provided by patients to interpret symptoms and provide preliminary diagnostic insights. Flask API and Deep Learning Pipeline: This connects the models to the frontend, allowing real-time predictions through secure API calls. It combines image and text analysis for a holistic approach to diagnostics.

7.4. UI and Web Application Module Built with Streamlit, this module provides an interactive user interface that enhances the overall user experience. Patients can enter personal details, upload dental images, and describe their symptoms in a guided manner. Doctors have access to dashboards where they can view and manage patient information and diagnostics. Additionally, an animated answering system resembling ChatGPT-style typing animations has been added to improve user engagement during interactions.

7.5. Integration and Communication Module This backend integration ensures smooth communication between different components. The Flask API acts as a bridge between the frontend and backend systems, facilitating secure data exchange for interactions like predictions. The requests module effectively handles communication between the Streamlit-based frontend and Flask backend. Overall, the system provides an efficient and streamlined solution for diagnosing dental issues and managing appointments. The dummy login functionality effectively showcases the capabilities of the application in a simulated environment, despite not being an actual authentication system.

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VIII. SCREENSHOTS OF NORAL- AI DRIVEN ORAL HEALTHCARE SYSTEM

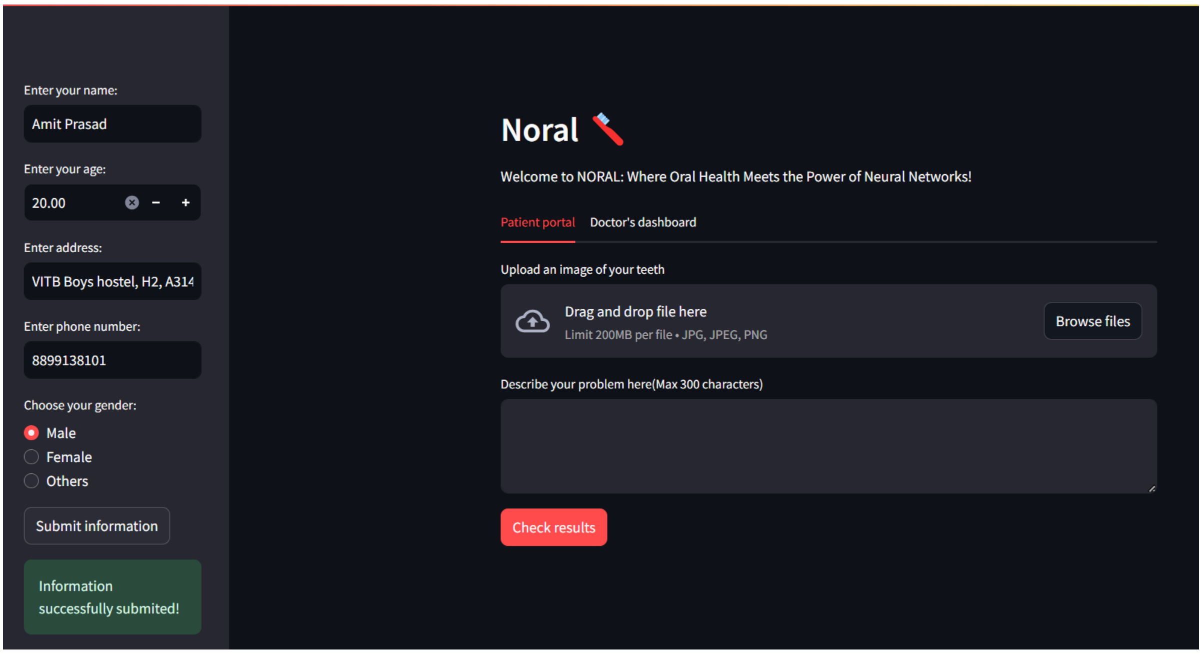

Figure-4: Noral- AI Driven Oral Healthcare System

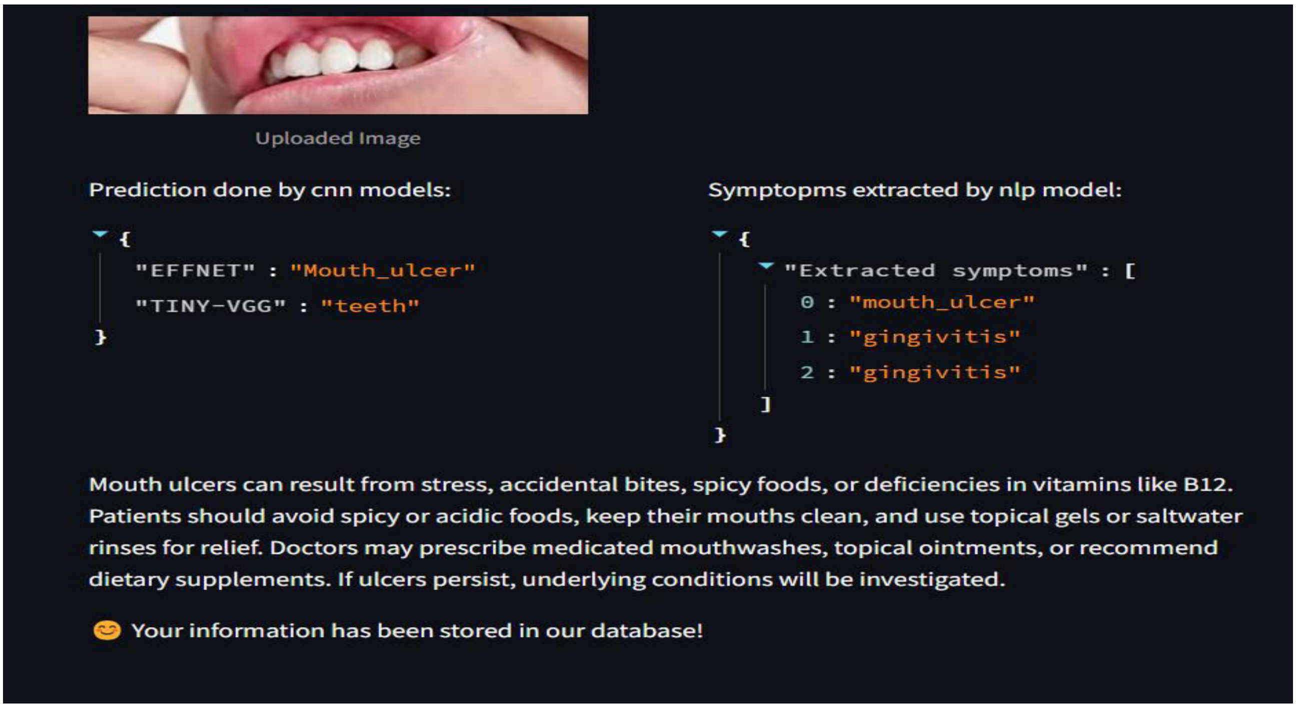

Figure-5: The patient portal Noral- AI Driven Oral Healthcare System

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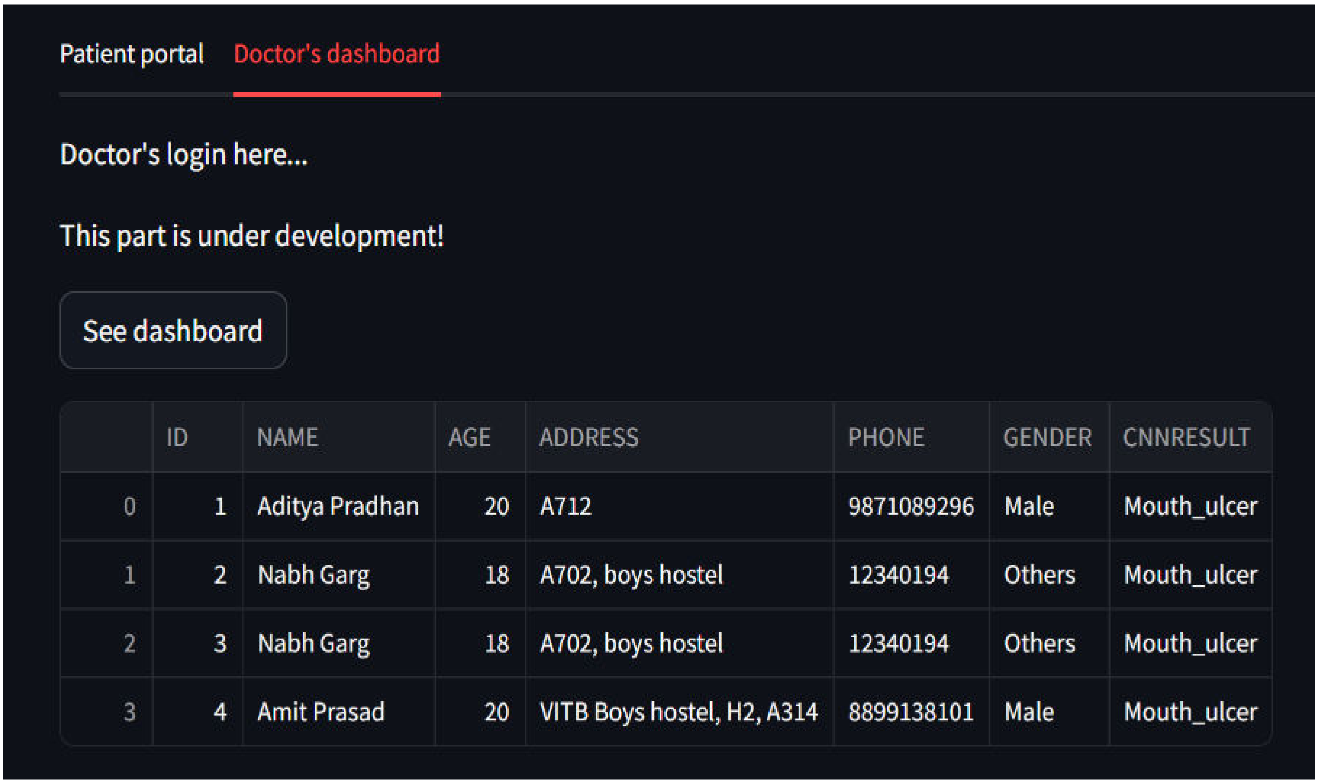
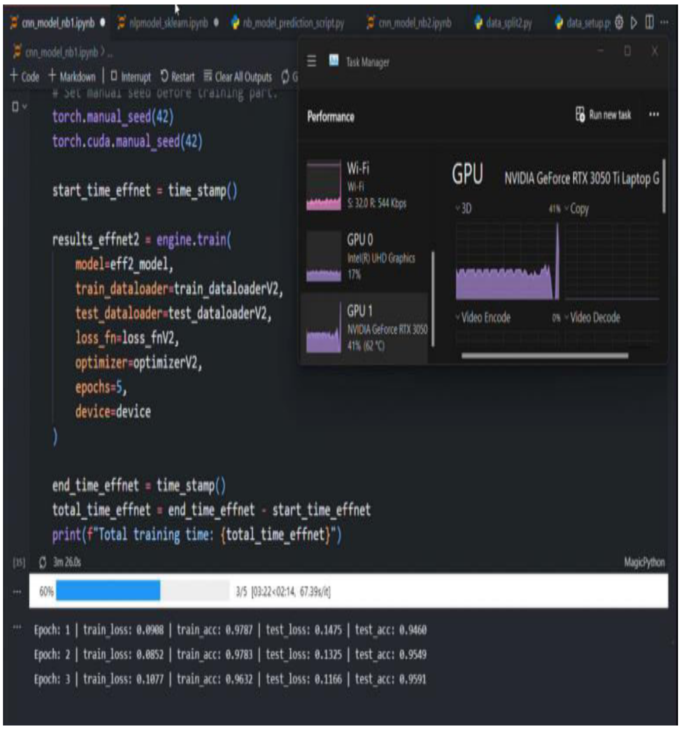


Figure-6: Screenshot of doctor's portal in which doctor can access the dashboard



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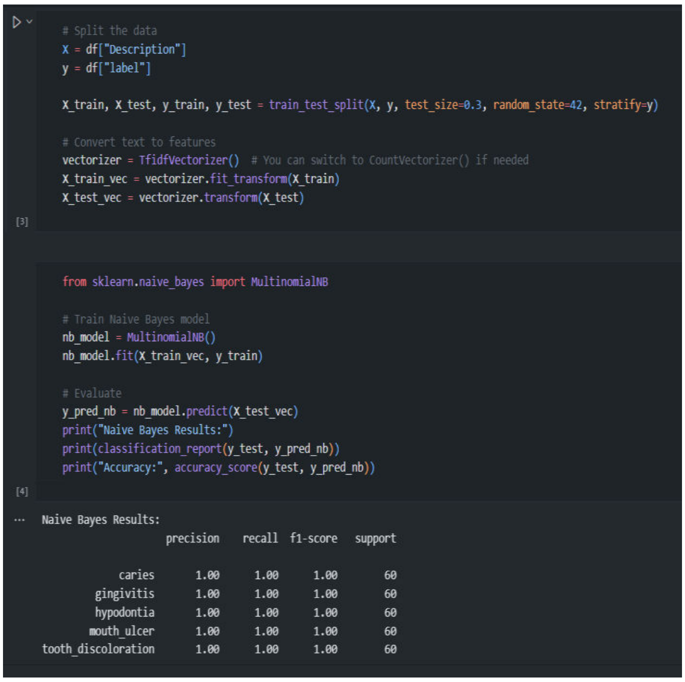
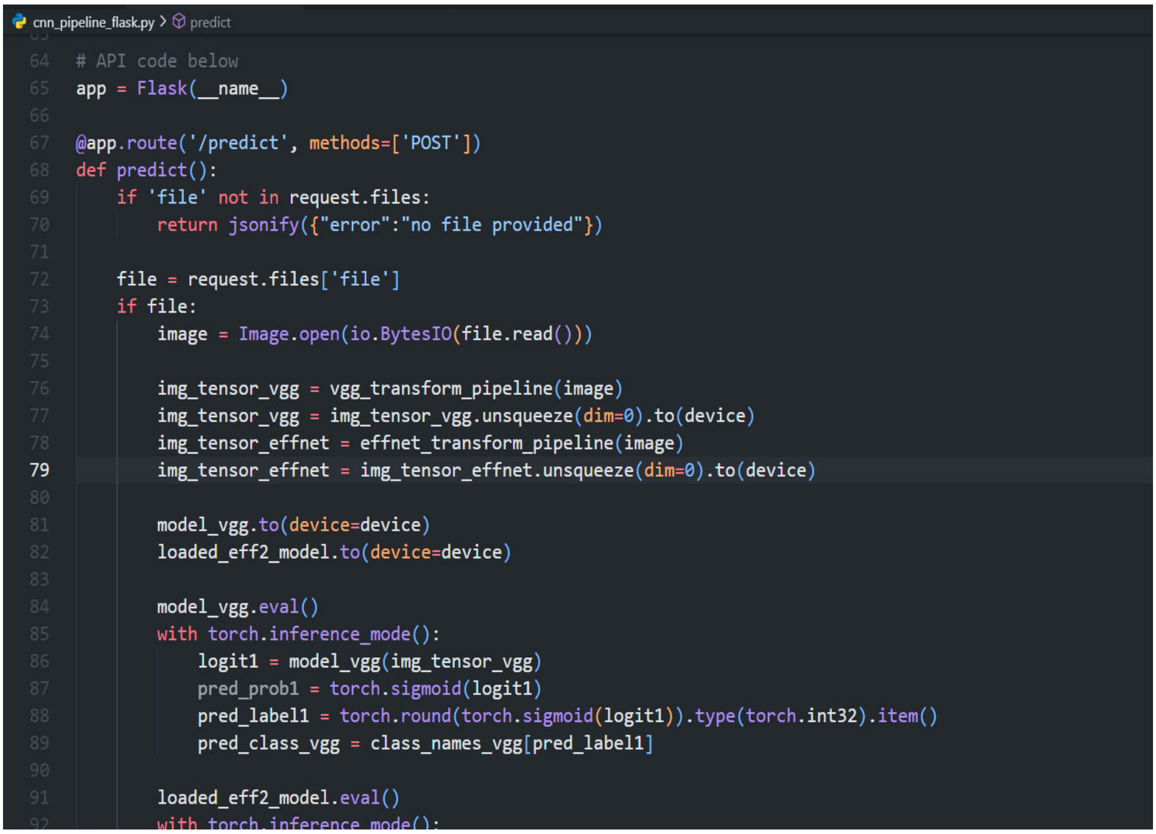


```
# Split the data
X = df["Description"]
y = df["label"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42, stratify=y)

# Convert text to features
vectorizer = TfidfVectorizer()  # You can switch to CountVectorizer() if needed
X_train_vec = vectorizer.fit_transform(X_train)
X_test_vec = vectorizer.transform(X_test)
[3]

from sklearn.naive_bayes import MultinomialNB

# Train Naive Bayes model
nb_model = MultinomialNB()
nb_model.fit(X_train_vec, y_train)

# Evaluate
y_pred_nb = nb_model.predict(X_test_vec)
print("Naive Bayes Results:")
print(classification_report(y_test, y_pred_nb))
print("Accuracy:", accuracy_score(y_test, y_pred_nb))
[4]

... Naive Bayes Results:
                    precision    recall  f1-score   support

           caries       1.00      1.00      1.00        60
       gingivitis       1.00      1.00      1.00        60
       hypodontia       1.00      1.00      1.00        60
      mouth_ulcer       1.00      1.00      1.00        60
tooth_discoloration     1.00      1.00      1.00        60
```

Figure-7: The Training of the models Noral- AI Driven Oral Healthcare System



```
cnn_pipeline_flask.py > predict
# API code below
app = Flask(__name__)

@app.route('/predict', methods=['POST'])
def predict():
    if 'file' not in request.files:
        return jsonify({"error":"no file provided"})

    file = request.files['file']
    if file:
        image = Image.open(io.BytesIO(file.read()))

        img_tensor_vgg = vgg_transform_pipeline(image)
        img_tensor_vgg = img_tensor_vgg.unsqueeze(dim=0).to(device)
        img_tensor_effnet = effnet_transform_pipeline(image)
        img_tensor_effnet = img_tensor_effnet.unsqueeze(dim=0).to(device)

        model_vgg.to(device=device)
        loaded_eff2_model.to(device=device)

        model_vgg.eval()
        with torch.inference_mode():
            logit1 = model_vgg(img_tensor_vgg)
            pred_prob1 = torch.sigmoid(logit1)
            pred_label1 = torch.round(torch.sigmoid(logit1)).type(torch.int32).item()
            pred_class_vgg = class_names_vgg[pred_label1]

        loaded_eff2_model.eval()
        with torch.inference_mode():
```

Figure-8: Noral- AI Driven Oral Healthcare System database connectivity and flask API Logic

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```python
app.py > ...
import streamlit as st
import os
from PIL import Image
import time
import requests

# Import for db connectivity
from dbutils import appreqs, dbread
from apputils.typewriter_effect import stream_data

temp_folder = "temp_files"
os.makedirs(temp_folder, exist_ok=True)

st.header("Noral 🪥")
st.write("Welcome to NORAL: Where Oral Health Meets the Power of Neural Networks!")

if 'info_submit_status' not in st.session_state:
    st.session_state.info_submit_status = False

with st.sidebar:
    name = st.text_input("Enter your name:")
    age = st.number_input("Enter your age:", value=None)
    address = st.text_input("Enter address:")
    phone = st.text_input("Enter phone number:")
    gender = st.radio(label="Choose your gender:",
                      options=["Male", "Female", "Others"], index=None)

    submit = st.button(label="Submit information")
    if submit:
        if name and age and address and phone and gender:
            st.session_state.info_submit_status = True
            st.success("Information successfully submited!")
        else:
            st.warning("Enter all the fields in order to proceed!")

tab1, tab2 = st.tabs(tabs=["Patient portal", "Doctor's dashboard"])
with tab1:
    uploaded_image = st.file_uploader(label='Upload an image of your teeth', type=['jpg', 'jpeg', 'png'])
    description = st.text_area(
        label="Describe your problem here(Max 300 characters)"
    )
```

Figure-9: Noral- AI Driven Oral Healthcare System Streamlit web application

IX. FINDINGS AND CONTRIBUTION OF Noral: AI DRIVEN ORAL HEALTHCARE

Noral: AI Driven Oral Healthcare Appointment System is a cutting-edge project that utilizes advanced technologies to streamline dental healthcare processes. Some key findings include.

9.1. Integration of AI in Dentistry

The implementation of Convolutional Neural Networks (CNNs) for dental image analysis has proven highly accurate, with a 97% success rate in identifying dental issues and validating images. Natural Language Processing (NLP) allows for the interpretation of patient symptom descriptions, providing initial recommendations.

9. 2. Efficient Workflow:

Automation of appointment management reduces reliance on staff and improves overall efficiency. A combination of CNN and NLP techniques offers a comprehensive diagnostic solution, considering both visual and textual inputs from patients.

9. 3. Effective System Design:

Developed using Streamlit for the frontend and Flask API for backend operations, ensuring efficient communication between components. Utilization of pre-trained models and fine-tuning methods has enhanced system performance for specific dental classifications.

9.4. Data Usage:

To address real-world data limitations, synthetic data was generated for NLP and publicly available datasets were used for CNN training.

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9.5 Limitations and Challenges:

Results are based on synthetic or publicly available datasets, requiring validation with real-world data.

o Overfitting may occur in controlled data environments, potentially affecting generalizability.

X. CONCLUSION

The project demonstrates the potential to revolutionize dental healthcare by combining AI technologies for diagnostic precision and efficient workflow management. However, real-world testing, dataset expansion, and user interface enhancements are essential for broader adoption and reliability in clinical settings. Future efforts should focus on validating the system in diverse environments, addressing generalization issues, and enhancing the scalability of the solution. The multiple functional modules, of the research project has specific role in efficiently managing dental healthcare workflows. These modules work together to create a comprehensive and user-friendly platform for automating dental processes. Our primary diagnostic model achieves an impressive 97% accuracy in detecting dental issues, while our auxiliary model has a 96% accuracy rate in verifying if the input image shows teeth. This ensures that only relevant inputs are processed, reducing errors and increasing reliability. Through the use of CNN-based ensembling techniques with hard voting, predictions from multiple models are combined to refine outputs and further improve accuracy. In addition, NLP capabilities interpret patient-provided symptom descriptions, providing initial advice and guiding diagnostics.

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