MALLA REDDY COLLEGE OF ENGINEERING AND TECHNOLOGY

SOFTWARE REQUIREMENTS SPECIFICATION (SRS)

for

DEEP LEARNING OF FACIAL DEPTH MAPS FOR OBSTRUCTIVE SLEEP APNEA PREDICTION

Version 1.0

Prepared by

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Title of the Project: Deep learning of facial depth maps for obstructive sleep apnea prediction

Content

Revisions

Version	Primary Author(s)	Description of Version	Date Completed
1.0	B. Veera Chary	Primary Revision giving an overall view of the project and document.	08/04/25

1 Introduction

Social and personal activities are significantly affected by poor sleep. There are different types of sleep disorders and it is costing us at different levels. As shows that only in Australia sleep disorder costs the economy around $5.1 billion per year that comprises health care, associated medical conditions, productivity, and non-medical costs. And among all sleep disorder, OSA is the most common cause. Normally during sleep, our upper airway remain open due to relaxed but strong enough muscles, lining the upper throat. But in OSA, someone can have a recurring blockage in upper airway due to different reasons, for more than 10 sec for each blockage, which causes the lungs out of oxygen and person to wake, which will restore the airway c. If more than 15 apneas occur then the diagnosis of OSA is made. History of the patient, physical examination, polysomnography(PSG) test, and imaging are being used to diagnose OSA. The gold standard to diagnoses is PSG test. In which a person needs to sleep in a unit in a hospital with some sensors to monitor breathing patterns, Oxygen level, heart rate, and body movements. Social and personal activities are significantly affected by poor sleep**.**

1.1 Document Purpose

This Software Requirements Specification (SRS) document is to develop a more accessible, cost-effective, and non-invasive method for diagnosing Obstructive Sleep Apnea (OSA) using deep learning techniques applied to facial depth maps. OSA is a prevalent sleep disorder characterized by repeated airway blockages during sleep, which can lead to severe health consequences, including cardiovascular disease, hypertension, and excessive daytime sleepiness. Current diagnostic methods, such as polysomnography (overnight sleep studies), are costly, time-consuming, and require specialized equipment, which limits their accessibility. As a result, many individuals with OSA remain undiagnosed and untreated.

1.2 Project/Product Scope

This project aims to explore the application of deep learning techniques in predicting Obstructive Sleep Apnea (OSA) severity using facial depth maps. OSA is a serious sleep disorder characterized by repeated airway blockages during sleep, typically due to the relaxation of airway muscles and the tongue. Traditional diagnostic methods, such as polysomnography, are expensive, time-consuming, and often inconvenient, leading to many undiagnosed cases. As facial morphology has been identified as a potential risk factor for OSA, this project proposes a novel approach using three-dimensional (3D) facial scans to analyze facial structures and predict the likelihood of OSA.

Ultimately, this research aims to provide a cost-effective, non-invasive, and accessible alternative to traditional OSA diagnostic methods. If successful, the developed system could be integrated into clinical settings or mobile applications, offering broader access to early OSA detection and contributing to better patient outcomes.

1.3 Existing System

The current standard for diagnosing Obstructive Sleep Apnea (OSA) is polysomnography (PSG), an overnight sleep study conducted in specialized sleep clinics or hospitals. During PSG, various physiological parameters such as brain activity (EEG), eye movement, muscle tone, heart rate, and respiratory effort are monitored to detect breathing disruptions, snoring, and oxygen desaturation levels. Based on this data, an apnea-hypopnea index (AHI) is calculated to measure the severity of OSA.

Alternatives like home sleep apnea tests (HSAT) offer a more convenient option, but they are less comprehensive and may miss mild to moderate cases. Furthermore, HSATs still require specific equipment and expertise to analyze the data

1.4 Problems with Existing System

1. High Cost: PSG is expensive, often costing hundreds to thousands of dollars per session, making it inaccessible to many patients, especially in low-resource settings.

2. Time-Consuming: The process involves staying overnight in a sleep clinic, which can be inconvenient for patients and create long waiting lists due to limited availability of specialized facilities.

1.5 Proposed System

The proposed system leverages deep learning techniques to predict Obstructive Sleep Apnea (OSA) severity using 3D facial depth maps, offering a non-invasive, cost-effective alternative to traditional diagnostic methods like polysomnography. This system aims to overcome the limitations of existing diagnostic techniques by utilizing facial morphology, which has been shown to be linked to OSA risk factors.

Key Components:

1. Facial Depth Map Analysis:

The system utilizes 3D facial scans, represented as depth maps, which capture the three-dimensional structure of the face in more detail than 2D images. Depth maps provide a more accurate representation of facial features and craniofacial structures that are associated with OSA, such as jaw alignment, airway size, and facial shape.

2. Deep Learning Model:

A convolutional neural network (CNN) is used to analyze the facial depth maps. Transfer learning, where a pre-trained model is fine-tuned on the OSA-specific dataset, enables the system to achieve high performance even with limited data. The model learns to extract relevant facial features from the depth maps that correlate with OSA severity.

3. OSA Severity Classification:

The system is designed to classify individuals into two categories: those with moderate-to-severe OSA (apnea-hypopnea index (AHI) > 15) and those with mild or no OSA (AHI ≤ 15). This binary classification allows for the identification of individuals who may require further clinical evaluation or treatment.

1.6 Advantages of Proposed Systems

1.Non-Invasive Diagnosis:

The proposed system utilizes facial depth maps, which are captured through 3D facial scans, making it a completely non-invasive method. Unlike polysomnography (PSG), which requires sensors and wires connected to the body during sleep, this approach is comfortable and eliminates the need for intrusive procedures, leading to higher patient compliance.

2. Cost-Effective:

Traditional OSA diagnostic methods, like overnight sleep studies, are expensive and often inaccessible. The proposed system offers a more affordable alternative by utilizing readily available 3D scanning technology and deep learning algorithms, significantly reducing the overall cost of diagnosis.

3. Time-Efficient:

The proposed system can provide rapid predictions based on a single 3D facial scan, eliminating the need for time-consuming overnight monitoring, which is required in traditional polysomnography. This allows for quicker diagnoses and earlier intervention for patients.

4. Wider Accessibility:

Since the system requires only a 3D facial scan, it can be easily integrated into both clinical and non-clinical settings. With the availability of depth-sensing cameras on smartphones and other consumer devices, the system has the potential to be used for home-based screening, making OSA diagnosis more accessible to a larger population.

5. Scalable Screening Tool:

The system can be used as a pre-screening tool for OSA in general healthcare or even through mobile applications. It provides an efficient way to identify individuals at risk of OSA without the need for specialized sleep clinics, thus enabling broader and more frequent screening.

2 Overall Description

2.1 Feasibility Study.

- **Technical Feasibility**

Availability of Technology :

3D facial scanning technology, which captures depth maps, is widely available and becoming increasingly affordable. Devices such as smartphones with depth-sensing cameras (e.g., Apple's Face ID technology) or 3D scanning tools can be used to collect data.

Deep Learning Model :

The use of convolutional neural networks (CNNs) for image analysis is well-established, and transfer learning allows models to achieve high performance even with limited data.

Data Availability :

Although medical datasets can sometimes be limited, there are opportunities to collect additional facial depth scans in both research and clinical settings. Transfer learning helps address the issue of small datasets by using pre-trained models on similar tasks.

- **Economic Feasibility**

Cost of Implementation :

The costs associated with 3D scanning technology have decreased significantly, making it affordable for both medical professionals and consumers. The use of widely available hardware such as smartphones further reduces the cost. Additionally, deep learning models can be run on standard computing devices or cloud-based platforms, minimizing infrastructure costs.

Return on Investment :

The system offers a significant return on investment by reducing the reliance on expensive polysomnography tests, which cost hundreds to thousands of dollars per session.

- **Social Feasibility**

Ease of Integration :

The proposed system is designed to be easy to use in both clinical and home environments. In a clinical setting, 3D facial scanners can be used as part of routine health checkups, allowing for quick pre-screening of OSA.

2.2 Product Functionality

The **Deep Learning of Facial Depth Maps for Obstructive Sleep Apnea Prediction** system provides an AI-driven solution for early detection and risk assessment of OSA using non-invasive facial analysis.

Automated Facial Depth Map Processing:
• Preprocesses raw facial scans to remove noise and standardize depth features across subjects.
• Aligns and normalizes facial depth maps for consistent analysis.

Facial Landmark Detection & Measurement Extraction:
• Extracts key anatomical features such as nasal width, jaw angle, and airway curvature using 3D depth data.
• Measures biometric indicators correlated with OSA severity.

AI-Based OSA Risk Prediction:
• Employs deep learning models (CNNs, ResNets) to analyze depth map features and predict the likelihood of OSA.
• Classifies subjects into risk categories (e.g., low, moderate, high) based on model confidence.

Medical Report Generation:
• Generates diagnostic summaries with risk scores, visual heatmaps, and explanations of key influencing features.
• Provides exportable reports for clinical documentation and further physician review.

Clinical Integration Support:
• Integrates with hospital and sleep clinic information systems (e.g., EHRs) for patient data access and automated scheduling.
• Supports batch processing for population-scale screening initiatives.

User-Friendly Medical Interface:
• Offers a clean, intuitive UI for uploading depth maps and viewing real-time diagnostic.

2.3 Design and Implementation Constraints

The development of the Generation and Detection of Face Morphing Attacks system must adhere to several key constraints to ensure performance, accuracy, and scalability.

Hardware & Performance Limitations

• The system must process 3D facial depth maps efficiently while maintaining high resolution and spatial accuracy.

• GPU acceleration or cloud-based computational resources (e.g., Google Colab, AWS EC2) will be necessary to train and infer deep learning models.

• Latency should be minimized to support near-real-time diagnostic feedback in clinical or telemedicine settings.

Software Platform

• The system will be developed in Python using AI frameworks such as **TensorFlow**, **PyTorch**, and **OpenCV** for depth data processing and analysis.

• All deep learning models must be optimized for medical use-cases, with efficient inference and minimal overhead.

• Development will follow best practices in AI lifecycle management, including model training, validation, and deployment workflows.

Modular Design

• The system should be modular to allow independent upgrades of components like depth preprocessing, feature extraction, or classification layers.

• Modules must be loosely coupled to support easy experimentation with different model architectures and preprocessing techniques.

• The architecture should support plug-and-play of new diagnostic algorithms or facial measurement tools.

User Interface (UI) and User Experience (UX)

• The UI must be intuitive for medical practitioners, technicians, and researchers with minimal technical training.

• Core functionalities such as depth map upload, risk report generation, and heatmap visualization should be integrated.

• Results must be presented clearly, including numerical risk scores and visual aids like colored facial overlays.

Data Management

• The system must ensure secure and structured storage of depth maps, patient metadata, and prediction outputs.

• Logging must capture system activity for auditing, model drift analysis, and patient traceability.

• Health data privacy must be enforced through anonymization and secure access controls.

Security Considerations
• Patient data must be protected using strong encryption protocols during both storage and transmission.
• Role-based access control (RBAC) must be enforced to restrict data access to authorized clinical personnel.
• The system must be hardened against adversarial attacks targeting AI vulnerabilities in facial analysis.

Compliance with Industry Standards
• The solution must comply with medical data privacy regulations (e.g., **HIPAA**, **GDPR**) and clinical data handling best practices.
• Model development should adhere to ethical AI guidelines to reduce demographic bias and enhance generalizability.
• The AI models should be trained and validated on demographically diverse datasets to improve diagnostic equity.

2.4 Assumptions and Dependencies

• **Familiarity with Medical Imaging Tools:** It is assumed that medical professionals and researchers using the system have a basic understanding of 3D imaging, facial analysis, and sleep apnea diagnostics.

• **Availability of Depth-Sensing Hardware**: The system assumes that facial depth data is captured using structured light, ToF sensors, or similar 3D imaging devices that offer high-resolution depth maps.

• **Support from Deep Learning Frameworks**: It is assumed that widely-used AI platforms such as TensorFlow and PyTorch will continue to offer compatible libraries for image preprocessing, CNN architectures, and model optimization.

• **Computational Infrastructure**: It is assumed that the development and deployment environments will include access to GPUs or cloud-based resources capable of handling large datasets and complex deep learning models.

• **Clinical Validation Support**: The system development assumes support from medical professionals for real-world validation, feedback, and ethical review of predictive accuracy and outcomes.

• **Timely Access to Annotated Datasets**: The training and evaluation processes assume access to labeled datasets of facial depth maps from individuals diagnosed with varying levels of obstructive sleep apnea.

Dependencies:

• **Depth Imaging Dataset Availability**: The system is dependent on the availability of diverse, high-quality depth map datasets from clinical trials or open-source medical research repositories.
• **Model Integration with Clinical Systems**: The final application may require integration with hospital management systems (HMS), electronic health records (EHR), or third-party diagnostic tools for seamless operation.
• **Updates in AI and Imaging Technologies**: Any major changes in the structure of depth-sensing technologies, or deprecation of core AI modules, could affect the performance or compatibility of the system.
• **Ethical and Legal Clearance**: Clinical deployment is dependent on adherence to health data protection laws (e.g., HIPAA, GDPR) and ethical approvals for using patient data.
• **Continuous Model Optimization**: The system relies on continued access to new data and research findings to refine model performance, reduce false predictions, and generalize across diverse populations.

Conclusion:

The **Deep Learning of Facial Depth Maps for Obstructive Sleep Apnea Prediction** system is designed to leverage advanced AI capabilities for non-invasive, early diagnosis of OSA. By addressing the outlined assumptions and dependencies, the system ensures scalability, clinical relevance, and high diagnostic reliability for real-world deployment.

3 Functional Requirements

3.1 Software Requirement Specifications

1. Operating System:

- Development Environment:
- Windows 10/11, macOS, or Linux (Ubuntu recommended) for model development, training, and testing.
- Deployment Environment:
- Cross-platform support for mobile applications, including Android or iOS, if the system is deployed for home screening.

2**. Development Tools & Libraries:**

- Python: Primary language for developing deep learning models.
- **Integrated Development Environment (IDE):**
- PyCharm, Jupyter Notebook, or VS Code for code development and testing.

3. Deep Learning Libraries:

- TensorFlow or PyTorch: For building and training convolutional neural networks (CNNs) and applying transfer learning.
- Keras: A high-level API built on TensorFlow for easier model development.

4. **Data Management Tools:**

- SQL or NoSQL Database: To store and manage the large amount of data generated during facial scans and model results.
- HDF5 or CSV: To store intermediate data, model weights, and results.

4. **Cloud Computing Services (Optional):**

Google Colab, AWS (Amazon Web Services) EC2, or Microsoft Azure: For scaling the model training if local computational resources are insufficient, especially when training deep learning models on large datasets.

3.2 Hardware Requirements Specifications

1. **3D Scanning Device or Depth-Sensing Camera:**

   Type: A device capable of capturing 3D facial data in the form of depth maps.

   Purpose: To capture high-resolution 3D facial scans for input into the deep learning model.

2. **Computing Device for Model Training:**

   Processor: Multi-core CPU (e.g., Intel i7 or higher) with support for parallel processing.

   Storage: Minimum 500GB SSD for fast data access and storing 3D facial scan datasets and model checkpoints.

3. **Computing Device for Model Inference:**

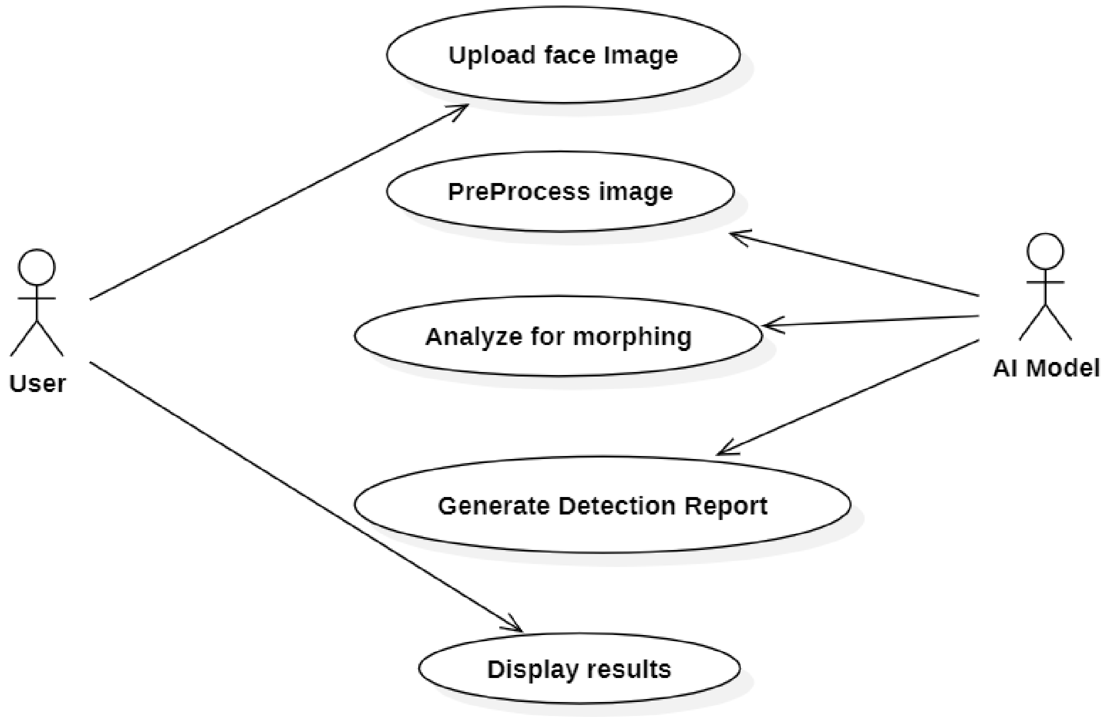
   Processor: Dual-core CPU or higher for running the trained model.

   Storage: 50GB SSD for storing the trained model and performing real-time inferences

4. **Mobile Devices for Deployment (Optional):**

   Smartphone or Tablet: For home-based screening, smartphones with depth-sensing cameras (e.g., iPhones with Face ID) are required to capture facial scans and perform real-time inference using lightweight models.

3.3 Use Case Model



3.3.1 Use Case #1 (OSA Detection Workflow – U1)

Author – Team OSA Detection Using VGG-19

Purpose – This Use Case Diagram provides a high-level overview of how a user interacts with the system to detect Obstructive Sleep Apnea (OSA) using a deep learning model (VGG-19).

Requirements Traceability

- **R1**: User uploads the OSA dataset.
- **R2**: Dataset preprocessing (cleaning, normalization, augmentation).
- **R3**: Construction and training of a VGG-19 model.
- **R4**: Upload of test data and prediction of OSA condition.
- **R5**: Visualization of model performance via accuracy comparison graph.

Priority – High

Preconditions –

- User has the OSA dataset available for upload.

Postconditions –

- The system completes prediction and displays the accuracy comparison graph.

Actors

- **User** (Medical Researcher, Data Scientist, Healthcare Professional)
- **System** (Deep Learning-based OSA Prediction Platform)

Extends – N/A

Flow of Events

1. Basic Flow

- The user uploads the OSA dataset to the system.
- The system preprocesses the dataset for model readiness.
- A VGG-19 model is built and trained on the dataset.
- The user uploads test data for prediction.
- The system predicts OSA conditions and displays results.
- The system generates an accuracy comparison graph for analysis.

2. Alternative Flow

- The user re-uploads the dataset if the initial upload fails.
- User may choose to apply custom preprocessing steps.

3. Exceptions

- Dataset upload fails due to incorrect file format or size.
- Preprocessing fails due to missing or corrupted data entries.
- Model training is interrupted due to resource constraints.

- Prediction fails if the test data is incompatible.

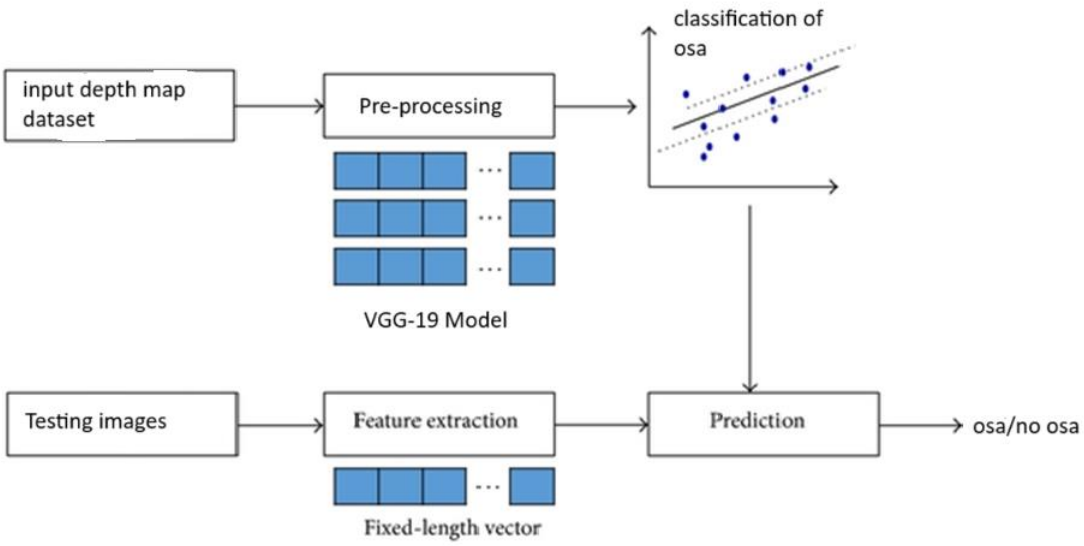
Includes

- Data preprocessing including normalization and augmentation.
- VGG-19 based deep learning model for OSA prediction.
- Graphical analysis of model performance metrics.

Notes/Issues

- Future iterations may include real-time OSA detection from wearable devices.
- Model comparison with other architectures like ResNet or Inception could be integrated.

3.3.2 Data Flow Diagram



4 Other Non-functional Requirements

4.1 Performance Requirements

To ensure an accurate, efficient, and scalable system for OSA prediction using facial depth maps, the following performance requirements must be met:

- **P1. Data Processing Speed**: The system must preprocess and analyze a single facial depth map within **5 seconds** to ensure real-time feedback capability.
- **P2. Batch Prediction Time**: For large clinical datasets (e.g., multi-patient scans), batch prediction should complete within **1 hour for 10,000 records**, ensuring timely diagnostic insights.
- **P3. Real-Time Feedback**: The system should provide OSA prediction results with **less than 2 seconds latency** after the depth map is uploaded and processed.
- **P4. Model Prediction Efficiency**: The deep learning model (e.g., VGG-19 or custom CNN) must deliver predictions within **1.5 seconds** per input to enable fast clinical decision-making.
- **P5. Accuracy & Performance**: The prediction model must achieve a minimum **accuracy of 90%**, with a balanced **precision and recall above 88%** to reduce misdiagnosis.
- **P6. System Scalability**: The platform must support processing of **up to 20,000 predictions per hour** in hospital or research environments under high-load scenarios.
- **P7. Cloud & Infrastructure Optimization**: The system should utilize **GPU-accelerated cloud environments (AWS, Azure, GCP)** for efficient model training and deployment, enabling auto-scaling and cost efficiency.
- **P8. UI Responsiveness**: User interface (e.g., web app or desktop interface) must load all modules and visualization reports within **1 second** to ensure a smooth user experience.
- **P9. Data Storage & Compression**: Facial depth map data and logs should be stored using **optimized formats (e.g., HDF5, NPZ)** and **compression algorithms** to minimize storage without loss of data fidelity.
- **P10. Security & Compliance**: All data (especially patient information and facial scans) must comply with **HIPAA, GDPR, and medical data standards**, employing **encryption during transmission and at rest**.

4.2 Safety and Security Requirements

Since the OSA prediction system processes sensitive facial scan data and potentially identifiable health information, the following safety and security measures must be implemented:

- **S1. Data Encryption**: All patient data, including facial depth maps, must be encrypted **in transit (TLS 1.2/1.3)** and **at rest (AES-256 encryption)** to prevent unauthorized access and data breaches.
- **S2. User Authentication & Access Control**: The system must implement **multi-factor authentication (MFA)** and **role-based access control (RBAC)** to ensure only authorized personnel (e.g., clinicians, researchers) can access patient data and model predictions.
- **S3. Data Anonymization & Privacy Compliance**: Any personally identifiable information (PII) must be anonymized or pseudonymized where applicable, ensuring compliance with **GDPR, HIPAA, and medical data protection regulations**.
- **S4. Intrusion Detection & Prevention**: The platform must incorporate **automated threat detection, firewall protection**, and **network monitoring tools** to safeguard against cyber-attacks and unauthorized access attempts.
- **S5. Secure APIs & Communication**: All communication with system APIs must use **secure authentication protocols (OAuth 2.0, JWT tokens)** and encrypted data transmission to prevent unauthorized interactions.
- **S6. Regular Security Audits & Monitoring**: The system should undergo **routine security audits, vulnerability assessments, and penetration testing** to proactively identify and mitigate potential security threats.
- **S7. Backup & Disaster Recovery**: Daily **automated backups** must be implemented with a **disaster recovery plan** ensuring a **maximum recovery time objective (RTO) of 15 minutes** in the event of data loss or system failure.
- **S8. Anomaly & Fraud Detection Mechanisms**: The system should include **AI-based anomaly detection** to monitor suspicious activity such as unauthorized data access or tampering with model predictions.
- **S9. Compliance with Healthcare Industry Standards**: The system must adhere to standards such as **ISO 27001**, **NIST Cybersecurity Framework**, and **HIPAA Security Rule** for healthcare IT systems.
- **S10. Logging & Audit Trails**: All critical actions (e.g., user login, data uploads, model executions) must be **securely logged with timestamps**, enabling full **audit trails** for security reviews and forensic investigations.

4.3 Software Quality Attributes

The following attributes are essential for ensuring the usability, maintainability, scalability, and reliability of the Generation and Detection of Face Morphing Attacks system.

4.3.1 Usability

Requirement:

- The user interface (UI) must be intuitive and accessible for healthcare professionals, researchers, and non-technical medical staff.

Implementation:

- Develop a simple, clean UI with drag-and-drop support for uploading facial depth maps.
- Display real-time progress indicators during preprocessing and prediction.
- Show OSA prediction results in both numerical and visual formats (e.g., graphs, heatmaps).
- Incorporate tooltips and help sections for non-technical users.
- Conduct usability testing with clinicians and researchers to ensure ease of use and accessibility.

Verification:

- Validation through **user feedback**, **usability surveys**, and **task-based testing** sessions.

4.3.2 Maintainability

Requirement:

- The system architecture should support seamless updates to deep learning models, dataset pipelines, and UI components.

Implementation:

- Apply **modular architecture**, separating components for preprocessing, model inference, evaluation, and visualization.
- Use **version control systems (e.g., Git)** for managing code changes and collaborative development.
- Provide **well-documented APIs** and workflows for updating models and integrating datasets.
- Implement **automated unit, integration, and regression tests** to detect issues early during maintenance.

Verification:

- Verified through **code reviews**, **automated test logs**, and **documentation audits**.

4.3.3 Adaptability (Design for Change)

Requirement:

- The system must be flexible and scalable to incorporate new facial analysis models, updated preprocessing algorithms, and integration with clinical systems.

Implementation:

- Design with **plug-and-play support** for loading different CNN models (e.g., ResNet, MobileNet).
- Allow **custom preprocessing plugins** for adapting to varied facial scan formats and resolutions.
- Expose **RESTful APIs** for interoperability with electronic health records (EHRs) and diagnostic platforms.
- Enable **cloud-based deployment** using platforms like **AWS, GCP, or Azure** for scalable performance.

Verification:

- Successful implementation and testing of new model integrations, preprocessing enhancements, and external system connections.

4.3.4 Reliability

Requirement:

- The system must ensure accurate and consistent OSA prediction with robust fault-tolerance and minimum downtime.

Implementation:

- Incorporate **comprehensive error-handling mechanisms** for file input, model failure, and API errors.
- Use **distributed processing** and **parallel batch execution** for large-scale inference tasks.
- Validate inputs and maintain **data integrity checks** throughout the pipeline.
- Perform **extensive performance and edge-case testing** to minimize false predictions.

Verification:

- Evaluation through **test case coverage reports**, **system stress testing**, and **real-world deployment metrics**.

5 Other Non-functional Requirements

This section outlines additional requirements essential for the development, deployment, and security of the Generation and Detection of Face Morphing Attacks system.

5.1 Database Requirements

- **R1. Patient Data Storage:** The system should use a secure and scalable database (e.g., PostgreSQL, MongoDB, or MySQL) to store patient profiles, facial depth maps, diagnostic results, and prediction histories.
- **R2. Data Logging & Audit Trails:** The system must log data processing steps, prediction outputs, and user access to ensure traceability, reproducibility, and compliance.
- **R3. Data Security & Integrity:** All stored health data must be encrypted and safeguarded against unauthorized alterations to maintain integrity and confidentiality

5.2 Internationalization Requirements (If Applicable)

- **R4. Multilingual Support:** The platform should provide multilingual options for medical practitioners and researchers accessing diagnostic reports or interfacing with the system.
- **R5. Regional Adaptation:** The AI models should be configurable to account for anatomical and demographic variations across different ethnicities and regions.
- **R6. Unicode Support:** The database and user interface must support UTF-8 encoding to properly handle international character sets and language-specific metadata.

5.3 Legal & Compliance Requirements

- **R7. Data Protection & Privacy:** The system must comply with healthcare regulations such as HIPAA, GDPR, and other medical data protection laws.
- **R8. Consent Management:** All patient data must be used only with informed consent, with clear options for users to opt out of data collection or model usage**.**
- **R9. Accessibility Standards:** The UI must meet WCAG standards to ensure usability for healthcare workers and patients with disabilities.

5.4 Reuse Objectives

- **R10. Reusable ML Models:** The OSA prediction models should be modular and reusable across other facial biometric or sleep disorder detection platforms.
- **R11. Scalable Cloud Infrastructure:** The system should support deployment on cloud environments (e.g., **AWS**, **Google Cloud**, **Azure**) to handle large-scale clinical data and simultaneous predictions.
- **R12. API-Based Data Access:** RESTful APIs should be provided for secure access to diagnostic reports and AI model results by hospital systems or third-party applications.

5.5 Development Environment Requirements

- **R13. Programming Stack:** The backend should be developed using **Python** (Flask/Django), with deep learning models implemented in **TensorFlow** or **PyTorch**.
- **R14. Version Control:** The development team must utilize **GitHub** or **GitLab** for code management, collaboration, and change tracking.
- **R15. Testing & Model Validation:** Robust unit tests (using **pytest**), model validation procedures, and integration tests should be executed regularly to ensure high accuracy and minimal bias.
- **R16. CI/CD Deployment:** Continuous Integration/Continuous Deployment (CI/CD) pipelines must be established for automated testing, model retraining, and seamless updates.

5.6 Documentation Requirements

- **R17. Code Documentation:** All AI models, APIs, and image processing scripts must include detailed documentation and inline comments.
- **R18. System Architecture Documentation:** The workflow, database schema, and API integrations should be well-documented.
- **R19. User Guide & Tutorials:** Provide step-by-step guides, FAQs, and visual tutorials for administrators using the detection system.
- **R20. Release Notes & Versioning:** Each software update must include version release notes, detailing new features, bug fixes, and performance improvements.

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SRS DOCUMENT REVIEW

CERTIFICATION

This Software Requirement Specification (SRS) Document is reviewed and certified to proceed for the project development by the Departmental Review Committee (DRC).

Date of SRS Submitted:	
Date of Review:	
Supervisor Comments:	
Supervisor Sign. & Date.	
Coordinator Sign. & Date	
HOD Sign. & Date	
Dept. Stamp	