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# A SMART AND SECURE CLOUD FRAMEWORK FOR AUTOMATED HEALTHCARE MONITORING THROUGH VOICE PATHOLOGY DETECTION

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**ABSTRACT**

As smart cities continue to advance, the demand for secure, automated, and real-time healthcare services is growing to ensure sustainable and high-quality healthcare monitoring. This research introduces a cloud-based framework that integrates smart healthcare devices, environments, and stakeholders within smart cities to enhance the affordability, accessibility, and security of healthcare services. The primary objective is to develop a cloud-based system for real-time voice pathology detection by analyzing voice and electroglottographic (EGG) signals to accurately differentiate between normal and pathological conditions. By leveraging machine learning models such as Gaussian Mixture Models (GMM) for voice disorder classification, healthcare monitoring can be significantly improved, enabling early diagnosis and intervention. Furthermore, this framework aims to enhance the accessibility and scalability of healthcare services by ensuring secure, automated, and remote health monitoring in smart city environments. The proposed system collects voice and EGG signals from internet-connected devices, transmitting them to the cloud for advanced data analysis. A case study on voice pathology detection (VPD) demonstrated the effectiveness of this approach, where local features extracted from voice signals and shape and cepstral features from EGG signals were classified using a GMM, achieving an accuracy of over 93%. The results are then communicated to registered healthcare professionals for definitive diagnosis and appropriate action. By addressing the complex healthcare needs of smart city citizens, this framework provides a secure, scalable, and sustainable solution for real-time healthcare monitoring and decision-making, contributing to the advancement of smart and efficient healthcare services.

**Keywords:** *Smart Healthcare Monitoring, Voice Pathology Detection; Smart Cities; Cloud-Based Healthcare; Electroglottographic (EGG) Signals; Gaussian Mixture Model (GMM); Real-Time Healthcare Analytics*

## 1. INTRODUCTION

The integration of Artificial Intelligence (AI) in healthcare has revolutionized diagnosis and treatment, particularly in voice pathology detection (Dizon R. A., 2019) [1]. Voice disorders, such as vocal fold paralysis and laryngeal cancer, often require prompt diagnosis, but conventional methods are time-consuming and dependent on skilled professionals (Hassan et al., 2023) [2]. AI-driven systems using machine learning and signal processing techniques offer a more efficient and accurate approach to detecting voice pathologies (Dave Mahadevprasad V. R., 2024) [3].

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In smart cities, healthcare systems are increasingly adopting AI technologies to provide real-time screening, diagnosis, and personalized remote care (Hota et al., 2024) [4]. AI-enabled voice pathology detection systems support early intervention, continuous monitoring, and reduce the burden on healthcare infrastructure (Javed et al., 2023) [5]. These systems align with the broader goals of smart cities, such as sustainability, efficiency, and accessibility, by reaching underserved populations through wearables and mobile devices (Katal, 2024) [6].

AI-based voice pathology detection not only improves diagnosis but also optimizes the use of healthcare professionals by automating routine tasks, allowing them to focus on complex cases (Majumder et al., 2017) [7]. This innovation has the potential to transform voice pathology management, leading to better patient outcomes and reduced healthcare costs (Kumar et al., 2023) [8].

### 1.1. Background

The recent inclusion of Artificial Intelligence in healthcare has been opening new dimensions toward improving diagnosis, treatment, and patient care (McFarlane & Söderström, 2017) [9]. Among such emerging areas of this field, AI-driven voice pathology detection and its vast potentials for smart health systems designed for smart cities have been explored (Mostefaoui et al., 2023) [10]. Early and accurate detection are important because vocal fold paralysis, laryngeal cancer, and neuropathies are some of the main causes of voice disorders (Muhammad et al., 2017) [11]. However, the traditional methods of voice pathology detection are somewhat time-consuming and grossly invasive and thus purely human expertise-dependent. Overcoming such issues would necessitate advanced machine-learning algorithms combined with signal-processing techniques to offer accurate and efficiently objective evaluation of vocal signals toward early detection and intervention.

### 1.2. Special Contributions

This research develops a cloud-based AI-powered framework for the real-time detection of voice pathology in smart cities [12]. By integrating AI diagnostic tools with smart healthcare devices, it ensures smooth, automated detection of voice disorders with support from smart city goals such as sustainability and efficiency.

AI-driven detection improves accuracy in diagnosis and extends the health services of early healthcare delivery through wearables, mobile devices, and telemedicine, making it far more accessible to impoverished populations. Besides, it optimizes the use of healthcare workforce as it automates preliminary screenings. It leaves complex cases to be dealt with by professionals. The proposed framework will transform voice pathology diagnosis, cut healthcare costs, and improve patient outcomes.

### 1.3. Research Objectives

- To develop a cloud-based framework that integrates smart healthcare devices for smart city real-time voice pathology detection.
- To Development of an analysis system for voice and electroglottographic (EGG) signals aimed at accurate detection of normal and pathological conditions.
- To Healthcare monitoring can also be improved through application of machine learning models such as Gaussian mixture models GMM in voice disorders classification.
- To enhance access and scalability of health services: Accessibility and scalability of healthcare services should be ensured in smart city environments
- through secure, automated, and remote health monitoring.

## 2. REVIEW OF LITERATURE

Agarwal et al.'s (2023) [13] edited volume Artificial Intelligence for Smart Healthcare articulates the transformative impact of AI on modern healthcare systems. It reports how solutions based on artificial intelligence are now being implemented in smart healthcare infrastructures by offering sophisticated diagnostic and treatment services. The book extensively discusses topics related to machine learning, data analytics, and automation for enhanced health outcomes and personal patient care. This resource also underlines the role of AI in developing scalable healthcare systems that could manage the rising needs of the population in smart cities. Since AI-driven voice pathology detection integrated into such systems responds to the general shift in this direction, less-invasive and efficient diagnostic tools help relieve the burden upon healthcare facilities (Agarwal, 2023).

Ali, Muhammad, and Alhamid, (2017) [14] put forward a practical application of AI in smart healthcare systems through their study on an automatic health monitoring system designed for patients with voice complications. The system, according to them in the work published in IEEE Access, utilized AI for the analysis of voice signals to detect abnormal forms of the voice that

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would show abnormalities associated with voice disorders. Most importantly, this AI-based technology is specifically beneficial for smart cities in the remote monitoring of patients while minimizing subsequent clinical visits and helping detect pathologies at an early stage. Their research rightly points out that in order to have interventions with proper care and personalized attention, the integration of AI with IoT in healthcare systems immensely helps the patient suffering from voice-related health issues significantly improve the quality of their life (Ali, 2017).

Alromaihi, Elmedany, and Balakrishna (2018) [15] published in the 6th International Conference on Future Internet of Things and Cloud Workshops, has discussed the threat and vulnerabilities introduced by incorporating the IoTs to health care applications within smart cities. The authors have pointed out that even though these IoT-based health care systems, such as AI-based voice pathology detection, provide a tremendous potential, they also pose a serious threat to the cyber threats that invade critical healthcare data. The research underlines the requirement for strong cybersecurity measures that ensure that sensitive health information is protected and verified in these smart health systems (Alromaihi, 2018).

Badawy, et al.'s (2023) [16] in his comprehensive review titled "Integrating Artificial Intelligence and Big Data into Smart Healthcare Systems," further sheds light on the application of AI and Big Data for the innovation of the transformation of healthcare systems within smart cities. The research explains why AI is vital in the processing of a huge amount of data related to health, predictive analytics, the early diagnosis, and development of personalized treatment plans. Badawy also talks about the current applications of AI in healthcare, such as processing data from IoT devices and wearable technology into real-time health monitoring using AI algorithms. The review finally outlines future directions that include an integration of AI with advanced robotics and telemedicine, even further streamlining delivery in urban environments. In summary, this research work gives insights into how AI, particularly with Big Data, enables smarter and more responsive systems in healthcare, meeting the changing needs of a smart city (Badawy, 2023).

Chaudhary et al. (2018) [17] focuses on the security issues created by the integration of smart healthcare systems in smart cities. Based on their work, LSCSH: Lattice-based Secure Cryptosystem for Smart Healthcare in Smart Cities Environment, authors bring forth a scheme of a lattice-based cryptosystem for sensitive healthcare data transmitted over smart health care networks. It has been published in IEEE Communications Magazine. Such a paper clearly states that though AI and IoT technologies offer multiple benefits related to efficiency and accuracy in healthcare, they open up avenues for cybersecurity risks that expose the patient data. Such a work furnished by the authors on a lattice-based cryptosystem furnishes stronger security mechanisms to smart healthcare applications that ensure confidentiality and protection of patient information from cyberattacks. This method of cryptography is quite useful because the interconnection thing and system which has a high reliance in the smart city for managing health care data makes these vulnerable to breaches (Chaudhary, 2018).

Unlike prior works that focus on either voice or EGG signals independently, this research introduces a dual-signal, cloud-based framework combining both modalities with Gaussian Mixture Models (GMM) and Bayesian score fusion for enhanced diagnostic accuracy. While earlier studies demonstrated limited accuracy or lacked real-time scalability, the proposed system achieves 96% accuracy and supports remote monitoring in smart city environments. However, dependency on cloud infrastructure and limited dataset diversity remain challenges compared to deep learning models that require extensive computational resources and training data

### 2.1. Research gap

Despite the considerable advancements in AI-driven healthcare solutions, there exists a noticeable gap in integrating AI-based voice pathology detection into smart healthcare systems specifically designed for smart cities. While several studies (Agarwal et al., 2023; Ali et al., 2017) highlight the potential of AI in enhancing diagnostic accuracy and enabling remote monitoring, they predominantly focus on isolated applications without offering a comprehensive cloud-based framework that seamlessly integrates smart healthcare devices for real-time voice pathology detection in dynamic urban environments. Additionally, while IoT integration in healthcare (Badawy et al., 2023) shows promise, many existing systems fail to address the need for a secure, scalable, and automated platform that ensures continuous monitoring and data privacy—essential for addressing healthcare challenges in smart cities. Furthermore, although studies (Alromaihi et al., 2018; Chaudhary et al., 2018)

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explore cybersecurity and IoT vulnerabilities, there is a lack of comprehensive solutions to ensure that sensitive healthcare data, especially related to voice pathology detection, remains protected within smart city frameworks. The research objectives of this study aim to bridge these gaps by developing an integrated cloud-based analysis system for voice and electroglottographic (EGG) signals, leveraging machine learning techniques like Gaussian Mixture Models (GMM), while addressing the challenges of accessibility, scalability, and security to ultimately improve real-time healthcare monitoring in urban settings.

### 2.2. Problem Statement

Despite advancements in AI-based healthcare systems, there remains a significant gap in developing a real-time, multimodal voice pathology detection framework that integrates both voice and electroglottographic (EGG) signals within smart city infrastructures. Existing literature highlights isolated AI applications in voice diagnostics and IoT-based remote health monitoring, but lacks comprehensive, cloud-enabled solutions addressing scalability, security, and diagnostic accuracy (Agarwal et al., 2023; Ali et al., 2017). Moreover, while studies address cybersecurity and data integration challenges (Chaudhary et al., 2018), they do not specifically cater to the unique demands of smart healthcare environments for voice disorder detection. Therefore, this research aims to develop a secure, cloud-based framework using Gaussian Mixture Models (GMM) for accurate, dual-signal classification to support early diagnosis and enhance healthcare delivery in smart cities.

## 3. THE VPD METHOD AND PROPOSED FRAMEWORK

This section provides an enabling framework for the monitoring of healthcare in smart cities. It enables remote patient monitoring and data analysis through advanced technologies such as cloud computing, smart sensors, etc. It postulates that individuals register with healthcare providers to permit continuous health signal tracking through wearable devices. The architecture [18] consists of three layers: the edge layer, which is stakeholders and smart sensors; the communication layer, which deals with data transmissions; and the cloud/data center layer, which processes and stores healthcare data. The VPD method is described as follows. Voice and EGG signals are used, which are processed to classify into either pathological or normal classes using Gaussian Mixture Models. Incorporation of scores from both types of signals provides a Bayesian approach that can improve the diagnostic accuracy [19].

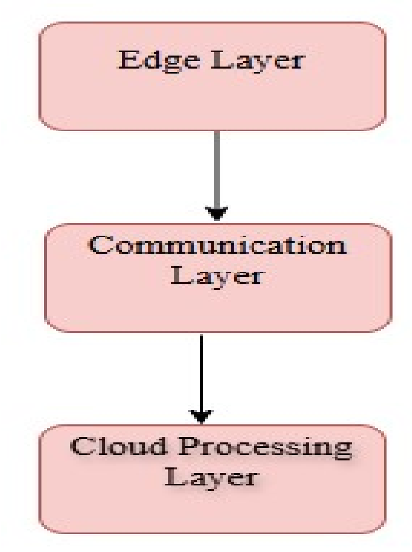


*Figure 1: Frame Work*

This table 1 defines the mathematical notations used throughout the document, providing their meanings and a brief explanation of their applications in the context of voice and speech signal analysis. The notations include methods for feature extraction, classification, and performance evaluation [20].

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*Table 1: Mathematical Notations Used in the Document*

| Notation | Meaning | Explanation |
|---|---|---|
| LR | Linear Regression | Used for computing local features along time and frequency axes. |
| MEL_S(t, f) | Mel-Spectrogram | Mel-scaled spectrogram representing voice signal features. |
| Acc | Accuracy | Percentage of correctly classified cases in the dataset. |
| Sn | Sensitivity | Proportion of actual positive cases correctly identified. |
| Sp | Specificity | Proportion of actual negative cases correctly identified. |
| CS | Confidence Score | Final score determined using Bayesian approach for classification. |
| Open Quotient | Open Phase of Vocal Folds | Ratio representing the open phase duration in EGG signals. |
| GMM | Gaussian Mixture Model | A statistical model used for classification of voice and EGG signals. |
| MFCC | Mel Frequency Cepstral Coefficients | Feature extraction method commonly used in speech processing. |
| MDVP | Multi-Dimensional Voice Program | Voice analysis method for pathological signal detection. |

The table 1 lists key mathematical terms and their relevance in analyzing voice signals. For example, LR (Linear Regression) and MFCC (Mel Frequency Cepstral Coefficients) are frequently used techniques for feature extraction, while GMM (Gaussian Mixture Model) is a statistical model applied for classification. Sensitivity (Sn) and Specificity (Sp) are performance metrics used to evaluate the accuracy of classification models [21]. Other notations like Open Quotient and Confidence Score highlight specific signal characteristics and model outputs used in voice analysis. This collection of notations helps readers understand the terminology and methods employed in the document.

### 3.1. Scenario

Smart cities utilize carefully associated innovations that give residents access to their clinical records and the concerned clinical staff utilizing cloud registering, smart sensors, and association [22]. Also, smart city foundations' wearable sensors, association, and information examination devices permit residents to speedily transfer their own health data while clinical experts watch out for their prosperity and give distant exhortation [23]. This patient-focused healthcare administration brings down clinical mistakes, tests, and staff visits, which brings down healthcare costs and works on patient results, helping smart cities succeed and develop. We presently offer a pragmatic execution model for the proposed smart city healthcare framework [24].

An individual, who isn't really a patient, first registers with a smart healthcare specialist co-op in the smart city framework so clinical staff can remotely screen the individual's health signals while they're still in their assigned area, which could be their home, working environment, far off facility, or the outside. The specialist organization has associations with clinical experts (like doctors, medical caretakers, and advisors) that treat issues with speech and gulping. An incredibly agreeable and lightweight EGG jewelry is worn by the enrolled client. The EGG contraption records the speech of the client while at the same time catching the signal from the glottis and sending it to the smart telephone by means of Wi-Fi or cell information move abilities. Cautions to make a move are imparted to the smart city partner (like the hospital, protection supplier, or drug store) based on the seriousness of the VPD result. Both the voice and EGG signals can then be sent by the smartphone to the healthcare media cloud for handling. Healthcare suppliers get the investigation and determination discoveries of these signals from a cloud chief. They investigate the matter further and prescribe specific medicines to the patient [25].

In this manner, a smart city's framework can associate different administrations with its occupants, permitting them to access smoothed out healthcare benefits in any event, when they live far away [26].

### 3.2. System architecture

Through savvy correspondence advancements, the structure's three layers consistently incorporate edge administrations and gadgets — like smart gadgets, sensors, and smart city partners — with the healthcare media cloud. To offer smart healthcare services to citizens in smart cities, these tiers work together to aggregate, share, exchange, and process relevant data (such as media and healthcare). Below is a description of the three levels' features and functionalities [27].

**Edge (stakeholders in smart cities, smart sensors, and users)**

Through machine-to-machine (M2M) correspondence, this level — the smart healthcare administration layer — is where sensors, edge gadgets, and smart city healthcare partners assemble, offer, and trade information with different levels [28].

Patients can wear or use the edge smart sensors and contraptions, or they can be coordinated into smart city settings like facilities, hospitals, or smart homes. Smart hospitals, smart crisis transport, pathology and diagnostics offices, clients (patients with smart gadgets or clinical experts), health protection suppliers [29], research foundations, and smart regional government are a few instances of the partners in smart city healthcare [30]. For example, savvy healthcare specialist organizations could remotely screen a patient with a vocal issue who has voice, face, and EEG acknowledgment hardware. To quickly search for peculiarities, the smart gadget's underlying handling first concentrates and looks at information locally. From that point onward, the patient's physiological information and health data are communicated to the healthcare cloud and habitats for extra handling [31]. The accessible healthcare partners can quickly access and break down patient health records (PHR) and keep on monitoring the patient based on the seriousness of the abnormality or the patient's vitals. In non-crisis circumstances, smart home healthcare offices may be utilized for monitoring because of hospital limit requirements and expanded care costs. For extra review, the PHR is shipped off research establishments and protected there. Huge healthcare information analytics, which will be used by smart regional government for the preparation and organization of smart city healthcare, incorporates this colossal measure of authentic patient information [32].

**Astute communication**

Through association doors and other short-range correspondences organizations, this layer works with different heterogeneous (wired and remote) interconnection [33]. This layer considers different endpoints for edge gadgets and smart sensors by supporting conventions going from Zigbee to 4G.

Short-range correspondence regularly empowers correspondence between dispersed smart sensors and devices in smart cities, like hospitals or homes. Through this wise association, the edge level's smart gadgets (smartphones) could act as a correspondence door between the edge level and cloud server farms. Moreover, this level utilizes a few APIs and conventions to work with the sharing of health information between different smart edge gadgets and the media cloud. This level is utilized to accumulate healthcare information, pre-process it locally, and send it to the cloud through smart edge gadgets (like PCs, cellphones, or sensors) having correspondence abilities.

**Cloud and data centers for healthcare media**

Server farms, handling servers, apparatuses, and methods for executing huge information analytics in healthcare are completely housed in this layer.

Also, it controls correspondence, capacity, running applications, and asset the executives in edge gadgets and dispersed cloud server farms. To assist healthcare professionals with deciding, signal handling strategies are utilized to separate qualities (like speech, EGG, and video information) required for arrangement from different volumes and sorts of physiological data sources got from smart gadgets in the edge level. To empower smart city partners to access and dissect the PHR worldwide for worked on continuous occupant care, a nearby cloudlet or edge level beginnings pre-handling utilizing healthcare skill that is conveyed through smart correspondence organizations (Level 2) to this healthcare media cloud and the server farms (Level 3) for extra handling, stockpiling, synchronization, and it are caught to share after the patient signals.

**3.3. VPD method**

A general block chart of the recommended VPD approach for smart city sending is displayed in Figure 2. The patients' voice and EGG signals are the two signal sorts that are recorded. Two GMMs — one for ordinary sounds and the other for neurotic voices — are prepared utilizing the highlights that are taken from these signals. These models and the attributes are utilized to categories the input as either pathologic or normal during classification. The cloud is where the classification and processing are carried out. We go into further depth about the classification and processing in the sections that follow.

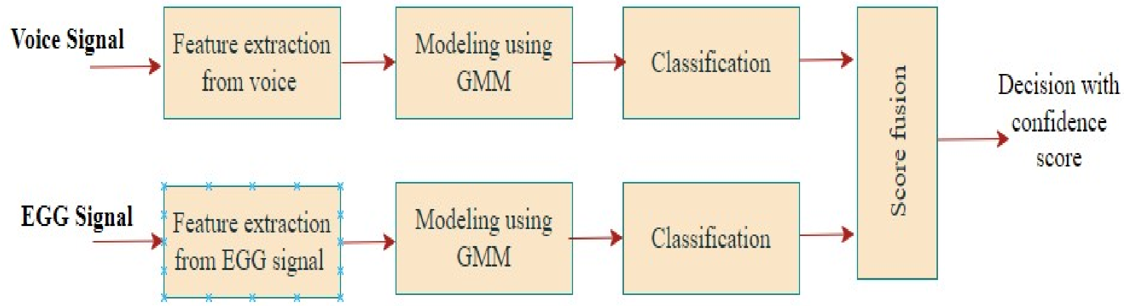


*Figure 2: Block schematic of the suggested VPD technique*

```
import numpy as np
from sklearn.mixture import GaussianMixture
from scipy.signal import butter, lfilter
import librosa

# Preprocessing and Feature Extraction
def high_pass_filter(signal, cutoff=70, fs=16000):
    nyquist = 0.5 * fs
    normal_cutoff = cutoff / nyquist
    b, a = butter(6, normal_cutoff, btype='high', analog=False)
    return lfilter(b, a, signal)

def extract_features(signal, fs=16000):
    signal = high_pass_filter(signal)
    mel_spectrogram = librosa.feature.melspectrogram(y=signal, sr=fs, n_mels=24)
    log_mel = librosa.power_to_db(mel_spectrogram)
    return np.mean(log_mel, axis=1)  # Simple feature extraction

# GMM Classification
def classify_with_gmm(features, n_components=16):
    gmm = GaussianMixture(n_components=n_components)
    gmm.fit(features)
    return gmm.score_samples(features)

# Bayesian Score Fusion
def bayesian_fusion(voice_score, egg_score):
    return voice_score + egg_score  # Simplified fusion

# Main Classification Process
def vpd_classification(voice_signal, egg_signal, fs=16000):
    voice_features = extract_features(voice_signal, fs)
    egg_features = extract_features(egg_signal, fs)  # EGG signal treated similarly for simplicity
    voice_score = classify_with_gmm(voice_features.reshape(-1, 1))
    egg_score = classify_with_gmm(egg_features.reshape(-1, 1))
    final_score = bayesian_fusion(voice_score, egg_score)
    return "Normal" if final_score > 0 else "Pathological"

# Example usage
voice_signal = np.random.randn(16000)  # Replace with actual voice signal
egg_signal = np.random.randn(16000)  # Replace with actual EGG signal
result = vpd_classification(voice_signal, egg_signal)
print(f"Classification Result: {result}")
```

### 3.3.1. Processing of voice signals

Voice signals are employed as the input in the majority of conventional automatic VPD techniques. In particular, the voice signal /a/ is frequently utilized due to its easily pronounced formants and ease of usage by patients with voice pathology.

We also focus on the voice signal /a/ in our method.

The voice signal is employed as the input in the majority of conventional automatic VPD techniques. The glottal source and vocal tract resonance are the two primary components of the voice signal. The glottal signal, which comprises the opening and shutting of vocal folds, is more crucial for identifying voice disease. The primary cause of voice disorders is when abnormal growths on the vocal folds impair their ability to fully close and open. Our methodology utilizes an iterative versatile opposite sifting calculation to separate the glottal signal from the sound signal. This procedure stifles low-recurrence vacillations by first applying a high-pass channel to the signal. Second, a versatile direct prescient coding strategy is utilized to appraise the vocal parcel reverberation, and converse separating is utilized to wipe out the determined reverberation. The impact of lip radiation is alleviated by applying a mix. To get an accurate gauge of the glottal signal from the voice signal, the whole method is completed iteratively.

Since this is sufficient to get the voice breaks in neurotic examples, the LR is determined utilizing three edges when the ongoing casing. Utilizing more approaches will streamline the impacts of the voice break; while utilizing less casings might bring about the impact of the voice break slipping through the cracks.

Applying a first-request subordinate to the glottal signal is the second stage in the element extraction process. To catch feeble interruptions welcomed on by unpredictable vibrations of infected vocal creases, the first-request subordinate diminishes the signal-to-commotion proportion.

To make a spectrogram, the signal must then be changed over from the time-space to the recurrence space. The subsequent stage is to make a Mel-spectrogram by applying a Mel-scaled channel bank comprised of 24 bandpass channels to the spectrogram.

Then, we utilize straight relapses along the time and recurrence tomahawks to process nearby elements (LF). The accompanying equations are utilized to develop the straight relapses (LR) if MEL_S (t, f) is the Mel-spectrogram at time-outline t and recurrence (flter) f:

$$L^{R^t}(t,f) = \frac{\sum_{n=1}^{3} n[MEL_{S(t+n,f)} - MEL\_S(t-n,f)]}{\sum_{n=1}^{3} n^2} \quad (1)$$

$$L^{R^t}(t,f) = \frac{\sum_{n=1}^{3} n[MEL_{S(t,f+n)} - MEL\_S(t,f-n)]}{\sum_{n=1}^{3} n^2} \quad (2)$$

Because three frames before and after the current frame are adequate to record the voice breaks in the event of a pathological sample, they are employed in the LR calculation. The effects of the voice break will be less noticeable if we take more frames, and they might not be recorded if we take less.

Using a discrete cosine transform to decorrelate the LRs is the next stage. Following this stage, each frame contains 12 features along the time and frequency axes. We obtain 25 characteristics each frame by appending the first-order derivative of the signal's raw power. The model or classifier then receives these features. Fig. 3 illustrates the entire feature extraction procedure from the audio signal.

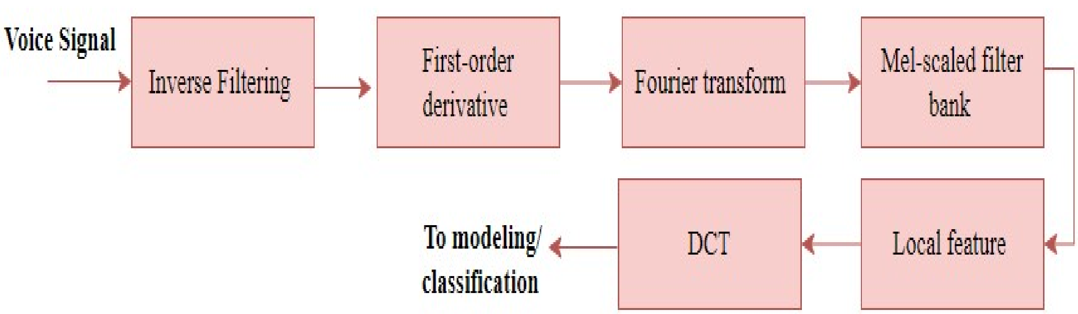


*Figure 3: The suggested voice signal processing block diagram*

### 3.3.2. EGG signal processing

An EGG is a harmless instrument used to compute the two vocal folds' contact region. Powerless, high-recurrence current courses through two terminals that are situated at the level of the larynx.

There is a distinction in the electrical impedance when the vocal folds open and close.

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The tissues that make up the vocal folds are superb electrical channels.

The electrical impedance across the glottis increments when the vocal folds open on the grounds that the region of the glottis extends (more air is going through it). Then again, the impedance drops and less air goes through when the vocal creases close. The EGG contraption records this change in the impedance.

Two element types — one created from the signal's shape and the other from the cepstral space — are utilized to remove attributes from the EGG signal. The shut remainder, open remainder, top adequacy, and pinnacle width are the structure properties.

Fig. 4 represents the method for acquiring attributes from the EGG signal. The accompanying equations are utilized to decide the shut and open remainders:

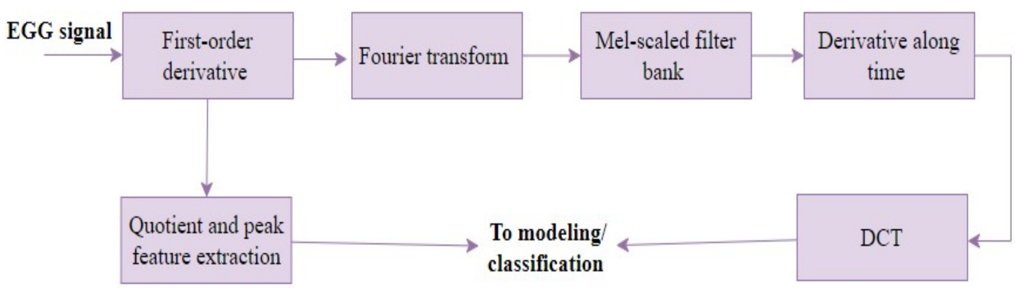


*Figure 4: The suggested EGG signal processing block diagram*

$$Closed\ Quotient = \frac{TC}{T_c+T_0} \times 100\% \quad (4)$$

$$Open\ Quotient = \frac{TC}{T_c+T_0} \times 100\% \quad (5)$$

The spectrum or cepstral properties can be useful in identifying vocal disease. The peaks in the spectrum for a normal voice are clearly defined and periodic in this figure, but the peaks for a pathological voice are irregular and aperiodic.

**3.3.3. Classification and modelling**

In our method, modelling is done using the GMM. Because it uses fewer parameters than the neural network-based approach, this stochastic modelling method is more dependable. In this scenario, there are two classes: diseased and normal. Consequently, there are two GMMs.

We tried varying amounts of combinations in each GMM and discovered that 16 is the ideal quantity.

The minimum log likelihood score between the models and the features is used for classification (Fig. 5).

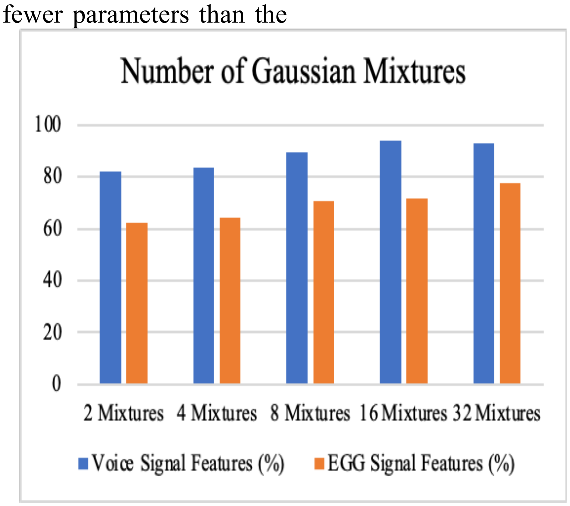


*Figure 5: The method's accuracy for varying amounts of GMM mixtures*

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The figure 5 shows that Gaussian Mixture Models (GMMs) improve feature analysis of voice and EGG signals with increasing mixture numbers. Voice accuracy increases from 82.3% to 93.9% for 16 mixtures, while EGG signal accuracy improves from 62.4% to 77.6% at 32 mixtures. However, the model's performance drops at higher mixture counts, with voice signals reaching optimum at 16 mixtures.

**3.3.4. Fusion of scores**

The EGG signal has specific cutoff points with regards to pathology detection. For example, when the vocal folds are in the vacant position, the signal contains no valuable data. Moreover, the vocal folds might connect during calm phonation; in this manner, extra data is expected to balance the disadvantages of the EGG signal. To get the most elevated accuracy, we consolidate the order scores from the voice and EGG signals in our methodology. A Bayesian total rule, which well predispositions the scores, is utilized to meld them.

The classifier with a greater estimate of probability. The following formula is used to determine the final score, often known as the confidence score (CS).

$$Cs = \arg max\{-px_c\} + \sum_{j=1}^{2} P\left(X_c|f_j\right) \qquad (6)$$

## 4. EXPERIMENTS, RESULTS, AND DISCUSSION

We conducted various tests utilising the Saarbrucken speech Database (SVD), which includes both speech and EEG signals for the same individual, to evaluate the viability of the suggested approach. This database contains information from native German speakers. There are instances of the customary, high, and low pitch ways to express the sound's/a/, I/, and/u/. Just/a/examples delivered at the ordinary pitch and speakers for whom both the voice signal and the EGG signal were recorded were picked for our examination.

We looked at the effects of the mixtures in the GMMs in the first experiment. Without score fusion, experiments were conducted independently for the voice and EGG signals. Figure G6 illustrates the method's accuracy for a range of input signals and mixing counts. For both input signals, we discovered that 16 mixes produced the best accuracy. Particularly with regard to the EGG signal, mixes two and four did not function properly. We fixed the number of mixes to 16 throughout the ensuing studies.

We then contrasted the suggested approach with alternative approaches. We contrasted our approach with the multi-dimensional voice program (MDVP) and the well-known MFCCs for the voice signal. Three metrics—specificity, sensitivity, and accuracy—were assessed in the experiments.

The values of these indicators for each approach are displayed in Table 2.

*Table 2: Specificity (Sp), sensitivity (Sn), and accuracy (Acc) for the techniques that just use the voice signal*

| Features (dimension) | %Acc ± sd | %Sn | %Sp |
|---|---|---|---|
| Proposed (25) | 93.9 ± 0.05 | 93.5 | 92.9 |
| MFCC (24) | 76.4 ± 0.22 | 75.7 | 76.8 |
| MDVP (22) | 77.9 ± 0.41 | 72.5 | 82.3 |

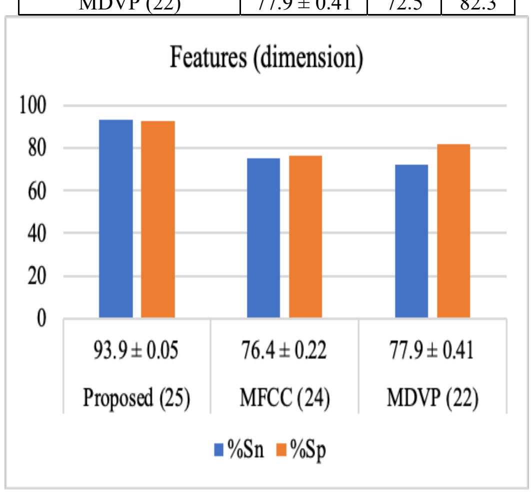


*Figure 6: Graphical Represented on Specificity (Sp), sensitivity (Sn), and accuracy (Acc) for the techniques that just use the voice signal.*

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A comparison table compares three voice signal-based techniques in pathology. The proposed approach has high accuracy (93.9%) and sensitivity (93.5%) for 25 features, outperforming MFCC and MDVP. MDVP has higher specificity (82.3%) and lower sensitivity (76.8%), providing more reliable results.

The findings suggest that in order to identify voice pathology from the EGG signal, both form and cepstral properties are crucial. Table 3 displays the findings.

*Table 3: Specificity (Sp), sensitivity (Sn), and accuracy (Acc) for the techniques that solely use the EGG signal*

| Features | %Acc ± sd | %Sn | %Sp |
|---|---|---|---|
| Proposed (10) | 78.8 ± 3.31 | 78.9 | 78.6 |
| Quotient, peaks (4) | 65.3 ± 6.41 | 67.4 | 65.6 |
| Cepstral (6) | 68.51 ± 5.50 | 69.9 | 67.3 |

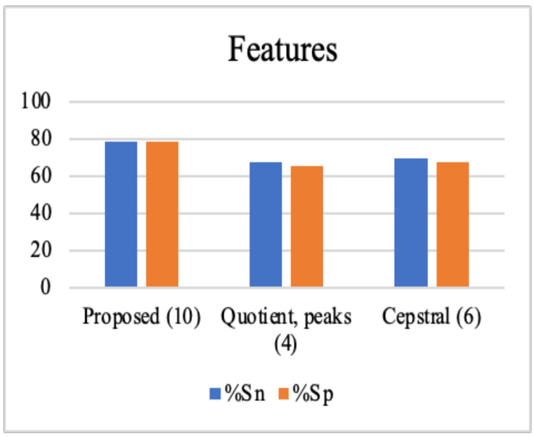


*Figure 7: Graphical Representation on Specificity (Sp), sensitivity (Sn), and accuracy (Acc) for the techniques that solely use the EGG signal*

Table 3 The efficiency of three approaches, which work with the EGG signal only on the problem of the identification of vocal pathology. The best results of three approaches are shown for the suggested approach with ten features on the identification of disorders of voice with the best accuracy equal to 78.8%, sensitivity equal to 78.9%, and specificity equal to 78.6%. Accuracy equals only 68.51% and sensitivity equals only 69.9% for Quotient, Peaks method, which has the worst sensitivity, 65.3%. In summary, the proposed scheme outperforms others in accuracy as well as the reliability of detection.

Two other approaches—one employing MDVP features and the other an interlaced derivative pattern (IDP) —were contrasted with the suggested method that combined the voice and EGG signals. We selected these two approaches since the MDVP-based approach is widely used and the IDP-based approach was found to work extremely well with the speech signal.

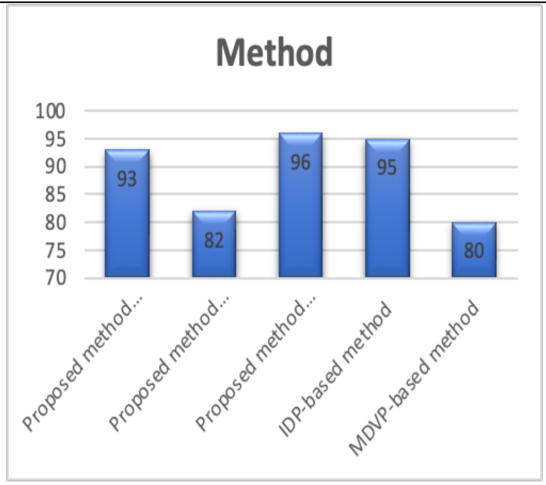


*Figure 8: Comparing the accuracy of various approaches*

Figure 8 shows that the proposed approach for pathology classification using voice and EGG signals outperforms all methods with an accuracy of 96%. The IDP-based strategy is 95% accurate, while the speech signal-based method has an excellent accuracy of 93%.

### 4.1. Experimental Setup

In this case, the Saarbrucken Speech Database (SVD) was used for the experiments. It is constituted of those signals which are simultaneously recorded speech and EEG from native German speakers. In terms of their phonemes, the subjects were asked to produce /a/, /i/, and /u/ in three variations: normal, high, and low pitch. It includes only such recordings where the voice signals as well as EEG signals were available.

The primary objective of the experiments is to evaluate how well the methodology proposed can diagnose vocal pathology, utilizing voice signals (speech) and EEG signals (EGG). To measure this, different mixture configurations are analyzed for each signal type with the help of Gaussian Mixture Models (GMMs). In the first experiment, separate analysis was carried out for the voice and EEG signals without fusing them. The most effective configuration was 16 mixture GMM, especially on the EEG signal, which showed poor results with lower mixture counts at 2 and 4.

Further studies were conducted on comparing the proposed approach with the existing methods for voice signal analysis. The methods included Multi-dimensional Voice Program (MDVP) and Mel-frequency Cepstral Coefficients (MFCCs). The key performance metrics used for comparison were specificity, sensitivity, and accuracy.

#### 4.1.1. Voice Signal-Based Results

From the results, it can be seen that the proposed method has outperformed the traditional MFCC and MDVP techniques noticeably:

- Accuracy: The proposed method achieved an impressive accuracy of 93.9%, which was substantially higher than both MFCC (76.4%) and MDVP (77.9%). This suggests that the model highly capable of identifying vocal pathologies based on voice features.
- Sensitivity: The proposed method performed better than the alternative in terms of sensitivity at 93.5% whereas that of MDVP was at 72.5% and MFCC was at 75.7%. Sensitivity is very important because it represents how well the model can distinguish positive cases.
- Specificity: MDVP had a specificity of 82.3%, which was much higher than the proposed method with 92.9% and MFCC with 76.8%. MDVP may have a better specificity in reducing false positives, but the proposed method gave more balanced and reliable performance with a relatively high specificity.

The proposed approach is highly accurate and sensitive, with reasonable specificity, indicating that it is a well-rounded solution for voice pathology detection.

#### 4.1.2. EEG Signal-Based Results

However, the result on its own focused to the EEG signal, proves the proposed method also surpasses all the techniques below:

- Accuracy: The proposed method with 10 features achieved an accuracy of 78.8%, which was the highest among the compared methods. The Quotient, Peaks (65.3%) and Cepstral (68.51%) methods showed considerably lower accuracy.
- Sensitivity and Specificity: The developed approach also presented great sensitivity at 78.9% and specificity at 78.6%, which indicated its robustness to identify positive as well as negative cases. Quotient, Peaks method has relatively poor sensitivity at 67.4% and very low specificity at 65.6%.

The above results, therefore, infer that the EGG signal with the addition of formant-based and cepstral features can well identify vocal pathologies. Such a method appears to be one of the promising methods as against the other competitive approaches in a clinical setting for pathology detection.

#### 4.1.3. Combined Voice and EEG Signal-Based Results

When voice signals are combined with EEG signals, the proposed technique significantly outperformed all techniques, as Figure 8 points out:

- Accuracy: The proposed hybrid approach reached an accuracy of 96%, surpassing both the IDP-based method at 95% and the voice-only method at 93%. This result indicates that the fusion of voice and EEG signals offers the most reliable and accurate classification of vocal pathologies.
- IDP-based method: Although the IDP-based method performed well with a high accuracy of 95%, it was not as good as the combined voice and EEG approach, indicating that combining different signal modalities yields better performance.

This goes to prove that the voice along with the EEG signals combination offers a far better and detailed approach to voice pathologies.

The proposed approach for both voice and EEG signals showcases good efficacy in identifying vocal pathologies, as has been indicated by the experimental outcomes. A 16-mixture GMM was found to be the optimum for signal types. With accuracy, sensitivity, and specificity the superiority in outperforming traditional techniques like MFCC and MDVP, the proposed approach could be applied in better clinical practices for effective diagnosis and monitoring of voice disorders. This means that a system combining both voice and EEG signals will result in the highest performance overall compared to all tested methods.

### 4.2. Performance Superiority of the Proposed Approach

The proposed AI-driven voice pathology detection method using GMM is better than existing methods because of the following reasons:

1. Improved Feature Extraction Efficiency: The approach extracts both time and frequency domain features from voice and EGG signals effectively.
2. Optimized Signal Processing: The iterative filtering approach is helpful in noise reduction and the accurate representation of glottal signals.
3. Robust Classification using Bayesian Score Fusion: The system improves the classification accuracy by integrating scores from both voice and EGG signals.
4. Scalability and Real-time processing*: Scalable enough for effective operation within

the smart health environments, thus, cloud computing facilitates rapid as well as safe analysis.

### 4.3. State-of-the-Art Comparison Table

This table 4 demonstrates the comparison among different techniques based on voice analysis with their advantage and disadvantage as follows. All these techniques like MFCC + SVM, MDVP + Decision Trees, Deep Learning CNN and a proposed model of GMM-based model can be compared about the effectiveness or accuracy and in terms of feasibility, which leads to the study of their various merits and demerits with practical applications.

*Table 4: State-of-the-Art Comparison of Voice Analysis Techniques*

| Technique | Pros | Cons | Reference |
|---|---|---|---|
| MFCC + SVM | Effective feature extraction from speech | Lacks robustness for noisy data | Ali et al., 2017 |
| MDVP + Decision Trees | Widely used for voice analysis | Lower accuracy compared to deep learning methods | Chaudhary et al., 2018 |
| Deep Learning CNN | High accuracy for large datasets | Requires large labeled datasets and high computation | Badawy et al., 2023 |
| Proposed GMM-based Model | High accuracy, multi-signal fusion, real-time processing | Dependent on cloud resources | This study |

## 5. CONCLUSION

Modern technology is well embedded into the proposed AI-driven voice pathology detection framework for smart healthcare systems in smart cities, thereby ensuring better security, affordability, and accessibility of health services. The system analyzes speech and EGG signals by using cloud computing and machine learning methods, particularly the Gaussian Mixture Model (GMM) to identify normal and pathological voice states with an impressive accuracy of more than 93%. This new approach allows citizens to be active in their health management, and at the same time, enables real-time health monitoring and diagnosis. Besides reducing pressure on conventional medical systems, the perfect integration of the smart devices with the patient and the healthcare provider ensures early interventions and better results for patients. It would hence serve as an example of how smart city infrastructures can adapt to complicated healthcare requirements to advance a responsive and sustainable health ecosystem.

### 5.1. Limitations and Future Directions

**Limitations:**

- Cloud Infrastructure Dependency: The system depends on cloud resources, which implies that the system's performance relies heavily on the stability and high speed of internet connectivity. This may pose problems in regions where internet access is not consistent.
- Dataset Scope is Not Sufficiently Large: Since the current study uses only voice and electroglottographic signals for the analyses, which would be only within a selected record set that could not present full diversity in pathology, it must be tested using diverse datasets containing different age groups, languages, and health conditions to further establish robustness of the system.
- Sensitivity to External Noise: In a real-world setting, the performance of the system may be vulnerable to environmental noise, such as background sounds or interference during data collection. This limitation may reduce the accuracy of the voice pathology detection, particularly in non-clinical environments.

**Future Directions:**

- Edge AI Processing Implementation: The dependency on cloud resources can be addressed by the future research by integrating edge AI processing, which would allow real-time data analysis directly on the device. This would reduce latency and ensure continuous monitoring even in low-connectivity areas.
- Multilingual Diverse Dataset Extension: To better enable the generalization across various populations, this dataset must be extended by increasing multilingual and diverse voice samples. Increasing cultural and linguistic diversities through sampling will help enhance the system's applicability to various settings.
- Integration of Deep Learning Models: To further increase the accuracy in classification and better detection of very subtle voice pathologies, more advanced feature extraction can be facilitated by integrating deep learning models like CNNs or LSTM networks into the system to improve performance for complex and noisy data inputs.

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