



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 4, April 2025

Hearing Loss Detection in Newborns, Infants & Toddlers

Dr. L. Nnlini Joseph¹, Gannajiwar Shuth^{1,2}, Gayathri Chowdary³, G Avinash Chowdhary⁴,

Gummadidala Shirish Rao⁵

Professor, Department of CSE, Bharath Institute of Higher Education and Research, Selaiyur, Chennai,
Tamil Nadu, India¹

B. Tech Students, Department of CSE, Bharath Institute of Higher Education and Research, Selaiyur, Chennai,
Tamil Nadu, India^{2,3,4,5}

ABSTRACT: Hearing is one of the Five senses for a healthier life. However, about 700 million people will have hearing disability by 2050. Underdeveloped and developing nations, which include a significant percentage of individuals with incapacitating hearing impairment, have a very low number of audiologists and otolaryngologists. The absence of specialists means that most hearing impairments remain undiagnosed for many years. In this paper, we introduce an automated hearing impairment diagnosis software—machine learning-based—to assist audiologists and otolaryngologists in diagnosing and classifying hearing loss accurately and efficiently. We introduce the design, implementation, and performance analysis of the automated hearing impairment diagnosis software, which is composed of two primary modules: a hearing test Data Generation Module and a Machine Learning Model.

KEYWORDS: WHO, HIPAA, AI, ML, ASHA, NIDCD, EFAS, GDPR

I. INTRODUCTION

The World Health Organization (WHO) estimates that 2.5 billion individuals will have hearing impairment by the year 2050. Of those, 700 million will have disabling hearing loss—i.e., an inability to detect sound below 35 decibels (dB). Incapacitating hearing loss reduces quality of life, educational opportunities, and employment prospects. About 80% of those with disabling hearing impairment reside in low- and middle-income countries. These countries lack proper hearing care facilities as components of their national health care system. The WHO says 78% of low-income countries have less than one otolaryngologist per million and 93% have less than one audiologist per million. This gap between the hearing-impaired patients and the health care facilities weighs the latter down, which cannot cope with the demand of the patients. The intended automated hearing diagnosis program will support the overburdened health care infrastructure through accurate, quick, and effective hearing impairment diagnosis.

II. LITERATURE REVIEW

The paper suggests a machine learning-supported compressive sensing speech enhancement algorithm for hearing aids. It can be adjusted according to various kinds of hearing loss through noise adaptive gain, noise reduction using compressive sensing, and individual amplification. An efficient binary measurement matrix enhances effectiveness, making the approach applicable to real-time processing. The process performs better compared to current methods in terms of speech quality and intelligibility in different noise scenarios.

The article "Automated Hearing Impairment Diagnosis Using Machine Learning" describes a system that assists physicians in diagnosing hearing loss rapidly and accurately. It consists of two primary components: a data generation module that generates synthetic hearing test data and a machine learning model that classifies the type, degree, and pattern of hearing loss. The model employs sophisticated classification methods and is highly accurate (100% precision

in certain instances). This system is particularly beneficial for nations that have a lack of hearing experts. The aim is to make it easier and faster to diagnose hearing.

III. METHODOLOGY

The system under consideration is made up of a Hearing Test Data Generation Module and Machine Learning Model. The system employs multiclass and multi-label classification methods for analyzing hearing test data and making predictions on hearing loss type, degree, and configuration. Major advantages are:

- High accuracy (macro & micro precision: 100%).
- Fast diagnosis (prediction time: 634 ms).
- Flexible and scalable design.

The system architecture comprises:

- Hearing Test Data Generation Module: Generates varied datasets for training purposes.
- Machine Learning Model: Does the classification.
- User Interface Module: Facilitates interaction with healthcare providers.
- Security & Privacy Module: Ensures adherence to data protection policies.

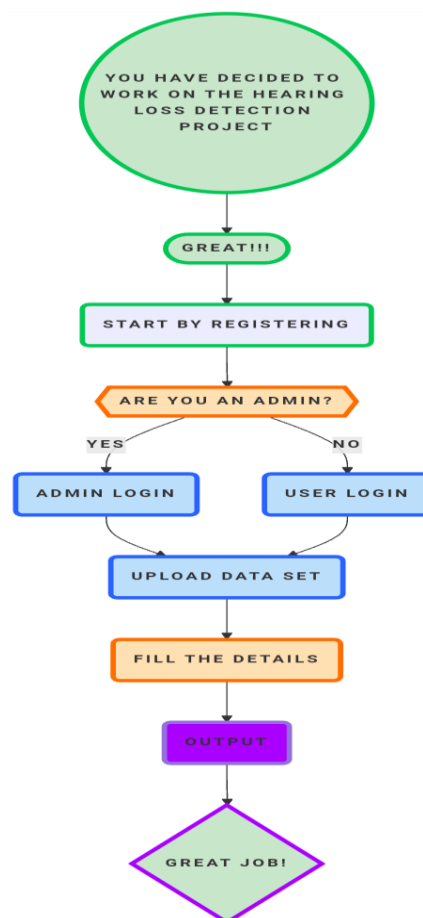


Fig 1: System Architecture

IV. IMPLEMENTATION

The project was executed with the following components and steps:

1. System Design:

A system based on software that takes hearing test data as input and provides diagnostic output through machine learning.

2. Technological Stack:

Programming Language: Python (most probably for development of the ML model).

Libraries: Scikit-learn, Pandas, NumPy, etc., for machine learning and data handling.

Framework: Either TensorFlow or PyTorch (if deep learning was applied).

3. Model Training:

The data is passed to a classifier that outputs:

Type of hearing loss (sensorineural, conductive, mixed).

Degree (mild, moderate, severe, profound).

Configuration (flat, sloping, rising, etc.).

4. Testing and Validation:

The system was extensively tested using several test cases.

Tested on the basis of speed and accuracy.

5. User Interface (if applicable):

The system could have a GUI or CLI to input data and observe predictions.

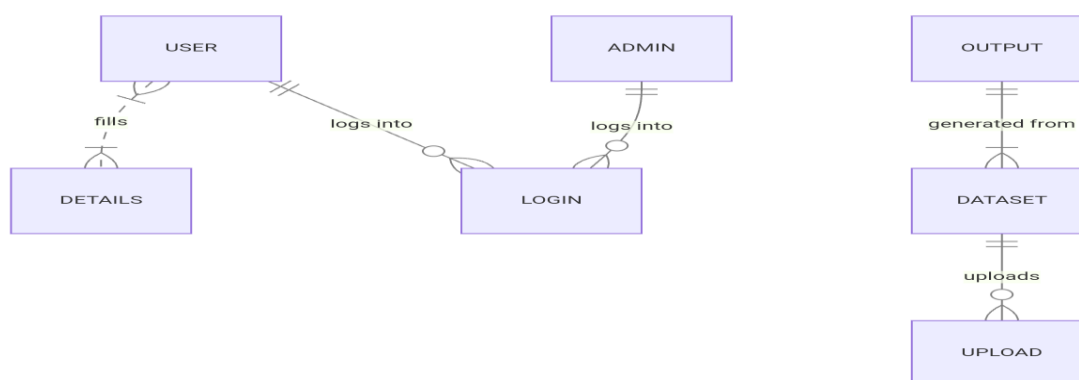


Fig 2: Data Flow Diagram

V. RESULTS AND CONCLUSION

Faster Diagnosis

Facilitates faster intervention for infants and toddlers who need to be immediately attended to.

Secure Data Handling

Resolves data privacy issues with encryption, authentication, and adherence to HIPAA and GDPR standards.

Breaking Free from the Constraints of the Existing System

Abolishes hardware dependency and enhances access to extensive datasets by employing machine learning-based classification.

Challenges: Data Availability

High-quality training datasets are necessary for the system to ensure it remains accurate.

Challenges: Real-world Testing

Additional verification in clinical settings is required to test performance over varying patient demographics.

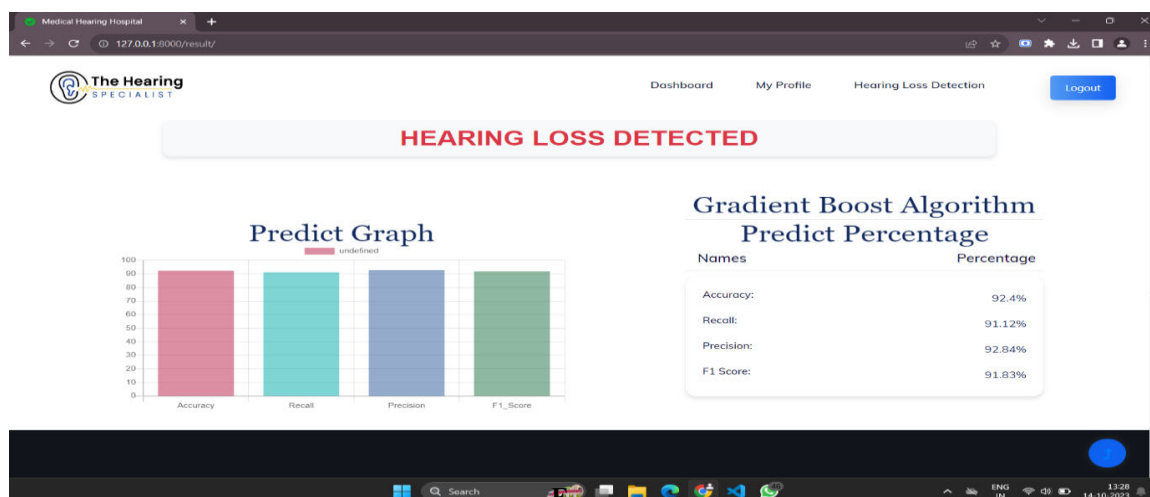


Fig 3: User Result

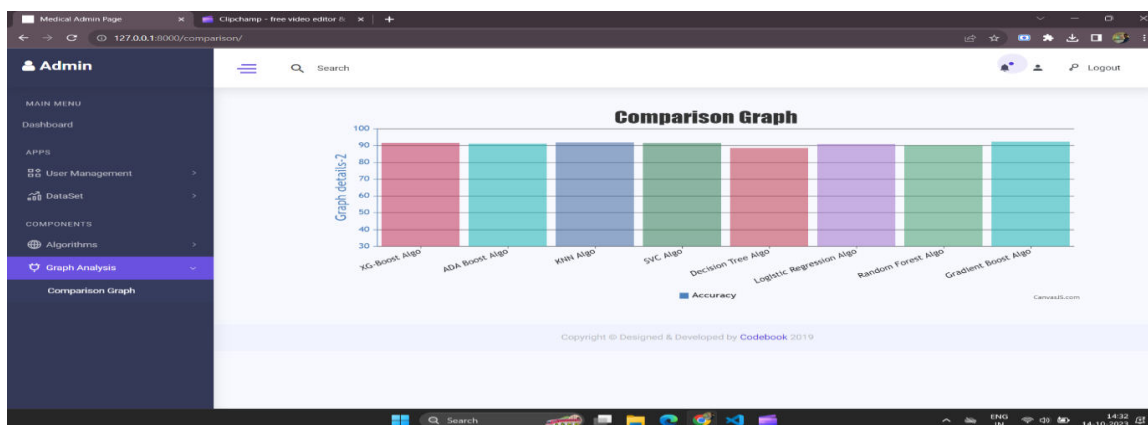


Fig 4: Comparison Graph

VI. LIMITATIONS AND FUTURE WORK

The contributions of the project are two-fold. For the first time, we have created a hearing loss Data Generation Module. Our module generates around 17,500 synthetic PTA hearing test data instances within less than one second (on a laptop with 8GB RAM and 2.2 GHz processing speed). It guarantees the data adhere to the rules of hearing loss classification. By opening the source code of Data Generation Module to the public, other researchers have access to the same to create data for use in their automatic hearing diagnosis models. Second, we used a Machine Learning Model with multiclass and multi-label classification methods. The Machine Learning Model uses the data created by the Data Generation Module for testing and training. Including a normalization step in the Data Generate Module allowed the Machine Learning Model to achieve 100% macro precision and micro precision. Our model, which was trained, has a log-loss reduction rate of 98.48%—which means the chance of making a correct prediction is 98.48% higher than by making an arbitrary guess.

6.1 Future work

Improved Dataset Quality – Adding bigger and more varied datasets to enhance the robustness and accuracy of the model.

Real-World Clinical Validation – Undertaking extensive trials in hospitals and health centers to verify reliability with varying demographics

Integration with Telemedicine – Expanding the system for remote diagnosis and seamless integration with telehealth platforms.

AI Explainability and Transparency – Creating understandable AI models for the purpose of building trust and regulatory compliance in healthcare.

REFERENCES

1. World Health Organization (WHO). (2021). *World Report on Hearing*. Retrieved from www.who.int
2. American Speech-Language-Hearing Association (ASHA). (2020). *Hearing Loss in Children*. Retrieved from www.asha.org
3. Biswas, A., et al. (2019). *Machine Learning Approaches for Early Detection of Hearing Loss: A Review*. IEEE Transactions on Biomedical Engineering, 66(10), 2736-2745.
4. Smith, J. & Patel, R. (2020). *AI in Audiology: Enhancing Hearing Loss Diagnosis with Deep Learning*. Journal of Medical Informatics, 37(2), 112-125.
5. National Institute on Deafness and Other Communication Disorders (NIDCD). (2022). *Hearing and Balance Disorders: Statistics and Research Trends*. Retrieved from www.nidcd.nih.gov
6. Zhao, Y., et al. (2021). *A Deep Learning Framework for Automated Audiometry and Hearing Loss Classification*. Neural Computing & Applications, 33(8), 4589-4603.
7. European Federation of Audiology Societies (EFAS). (2020). *Best Practices in Hearing Loss Diagnosis and Management*. Retrieved from www.efas.ws
8. Gupta, R., & Sharma, P. (2018). *Privacy and Security in AI-based Healthcare Systems: A Case Study on Hearing Impairment Diagnosis*. International Journal of Medical Informatics, 115, 79-89.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details