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Prediction of hearing recovery with deep learning algorithm in sudden sensorineural hearing loss

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This study aimed to establish a deep learning-based predictive model for the prognosis of idiopathic sudden sensorineural hearing loss (SSNHL). Data from 1108 patients with SSNHL between January 2015 and May 2023 were retrospectively analyzed. Patients underwent standardized treatment protocols including high-dose steroid therapy and hearing outcomes were assessed after three months using Siegel's criteria and the American Academy of Otolaryngology-Head and Neck Surgery (AAO-HNS) classification. For predicting patient recovery, a two-layered classification process was implemented. Initially, a set of 22 Multilayer Perceptrons (MLP) networks was employed to categorize the patients. The outcomes from this initial categorization were subsequently relayed to a second-layer meta-classifier for final prognosis determination. The validity of this methodology was ascertained through a K-fold cross-validation procedure executed with 10 distinct splits. The prediction model for complete recovery, based on Siegel's criteria, demonstrated an accuracy of 0.892 and area under the curve (AUC) of 0.922. For the class A prediction, according to AAO-HNS classification, the model showed an accuracy of 0.847 and AUC of 0.918. These results suggest that the model may have the potential to contribute to the establishment of tailored patient management strategies by predicting hearing recovery in patients with SSNHL.

Keywords Sudden hearing loss, Prognosis, Deep learning, Artificial intelligent

Idiopathic sudden sensorineural hearing loss (SSNHL) is an otologic emergency characterized by sudden, unexplained hearing loss. If left untreated, this condition can cause permanent hearing impairment, and ultimately diminish the patient's quality of life. Several possible factors have been suggested as causes of SSNHL, including viral infections, autoimmune inner ear disease, ototoxic medication, vascular problems, auditory tumors, and head trauma[1,2]. However, the exact underlying cause remains unknown despite extensive research. Due to this uncertainty, empirical treatment strategies are often employed for SSNHL, with high-dose steroid therapy commonly used due to its potent anti-inflammatory properties[3,4]. However, individual patient responses to steroid treatment vary, emphasizing the need for individualized management strategies.

One of the key challenges in managing SSNHL is predicting treatment outcomes or prognoses, so that a personalized, more aggressive interventions for patients with anticipated poor outcomes. The diversity of etiologic theories and patient-specific factors often results in a broad spectrum of recovery rates, highlighting the necessity for a more sophisticated, data-driven approach to prognosis prediction. Conventional approaches have relied on identifying clinical and audiological markers associated with hearing recovery. These often utilize extensive laboratory data that is not readily available in clinical settings and tend to focus on individual markers. Previous studies have revealed factors such as initial hearing levels, patient age, time between symptom onset and treatment initiation, high frequency hearing loss and the presence of vertigo as significant predictors of hearing

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recovery[5–11]. Nevertheless, due to the intricate interplay of these variables and inherent variability in patient responses, accurate prognosis prediction remains challenging.

Recent advancements in machine learning, particularly deep learning algorithms, offer promising ways to improve prognostic accuracy in medical decision making. These algorithms have the potential to analyze large data sets to identify patterns and correlations that may be too complex for traditional analysis techniques. Therefore, this study aimed to construct a predictive model based on deep learning algorithms for the prognosis of SSNHL. By utilizing a substantial dataset, we also aimed to overcome the limitations inherent in previous studies, identify important prognostic factors, and improve the accuracy of prognostic prediction in this complex otologic emergency.

Materials and methods

Study design and data collection

This study retrospectively collated data from idiopathic SSNHL patients who visited our tertiary center between January 2015 and May 2023. Medical records containing basic characteristics of patients, comorbidities, associated symptoms, initial hearing levels on the affected and unaffected sides, and final hearing levels were meticulously reviewed. The diagnosis of SSNHL was defined according to the 2019 Academy of Otolaryngology-Head and Neck Surgery (AAO-HNS) guidelines[1], indicating a hearing loss of 30 dB or more at three consecutive frequencies within 3 days.

As per the standardized treatment protocol, SSNHL patients initially received a high dose of oral steroids, with prednisone administered at 1 mg/kg daily for 7 days, followed by a 4-day tapering period. Subsequently, individuals who did not achieve a serviceable hearing threshold (< 40 dB HL) within one week underwent salvage intratympanic dexamethasone injections (5 mg/mL), administered four times every two weeks. Patients with diabetes followed the same treatment protocol for SSNHL, including hospitalization for glycemic control. In addition, patients with other underlying conditions received appropriate management alongside their treatment for SSNHL. Patients diagnosed with conductive hearing loss, Meniere's disease, or those with confirmed retro-cochlear lesions were excluded from the analysis. Additionally, patients who were treated exclusively with intratympanic injections without systemic steroids were also excluded. Finally, a total of 1108 patients were included in the study.

Selection of clinical parameters

For the prediction of treatment outcomes, clinical data comprising 20 parameters were utilized. These parameters include age, gender, comorbidities (hypertension and diabetes), lesion side, accompanying symptoms (vertigo, tinnitus and ear-fullness), initial hearing thresholds on the affected side (at 500 Hz, 1000 Hz, 2000 Hz, 4000 Hz), word recognition score (WRS) on the affected side, hearing thresholds on the unaffected side (at 500 Hz, 1000 Hz, 2000 Hz, 4000 Hz), and WRS on the unaffected side. Continuous variables like age and hearing thresholds were analyzed using measured values, while categorical parameters like comorbidities and accompanying symptoms were coded as binary (0/1) to construct the dataset.

Assessment of outcomes

Pure tone audiometry in the frequency range of 250–8000 Hz was conducted for all patients at initial visit and 3 months post-treatment. The average values of hearing thresholds (dB) at 0.5, 1, 2, and 4 kHz were calculated. The degree of hearing recovery was categorized as follows based on Siegel's criteria[12]: complete recovery, defined as a post-treatment hearing threshold of 25 dB or less; partial recovery, characterized by an improvement of 15 dB or more and a post-treatment hearing threshold between 25 and 45 dB; slight recovery, indicating an improvement of 15 dB or more but with a post-treatment hearing threshold greater than 45 dB; and no improvement, indicating an improvement of less than 15 dB or a post-treatment hearing threshold of 75 dB or greater. Additionally, the final hearing levels were classified according to the AAO-HNS classification[13]: Class A indicated hearing thresholds of 30 dB or less with a word recognition score (WRS) greater than 70%; Class B indicated hearing thresholds above 30 dB but not exceeding 50 dB, with a WRS of at least 50%; Class C indicated hearing thresholds exceeding 50 dB, with a WRS of at least 50%; and Class D indicated any hearing threshold with a WRS below 50%. Due to the clinical importance of achieving optimal hearing recovery, our analysis focused exclusively on the binary classification of complete recovery according to Siegel's criteria or class A according to the AAO-HNS classification.

Classification networks

To predict hearing outcome, we constructed 2-layered classification architecture. The first layer, comprised of 22 distinct Multilayer Perceptron (MLP) networks, differentiates patients into two categories: those who have achieved complete recovery and those who have not. These networks can be categorized into three distinct types based on the quantity of linear layers they incorporate: specifically, 4, 5, and 6 layers, as outlined in Fig. 1. To further illustrate, it is noteworthy that each linear layer, excepting the concluding layer, is succeeded by successive applications of ReLU (Rectified Linear Unit) activation, dropout, and batch normalization. This sequence of transformations serves the purpose of ameliorating the issue of overfitting. For the last layer, sigmoid activation function is utilized in order to give the prediction. (Fig. 1).

Subsequently, the classification results are further conveyed to the second layer, referred to as the metaclassifier. When exclusively employing the prognosticative capacity of the classifiers within the initial layer for patient outcome prediction, the attained accuracy and stability were deemed suboptimal for practical application within the field. In order to solve the problem, we adopted an approach wherein the outputs generated by the first layer

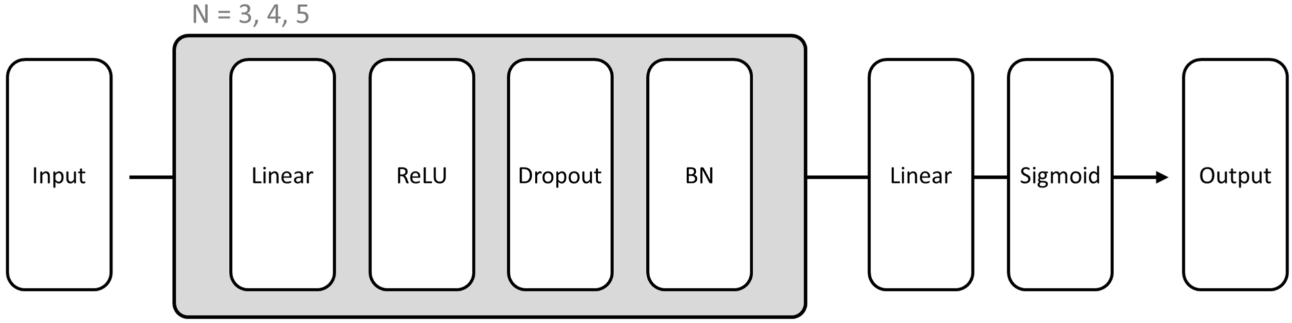

Figure 1. Schematic view of a Multilayer Perceptron (MLP) network used for prediction. ReLU, Rectified Linear Unit; BN, Batch normalization.

were channeled into a random forest classifier. In this manner, our work achieves much higher accuracy compared to only using one MLP network[14,15].

Combined loss function

Due to the limited and unique nature of medical data, it is essential to learn intricate inter-data relationships in addition to learning the overall distribution of the data. To achieve this, our work combines cross entropy loss with contrastive loss function[16]. Figure 2 shows overall mechanism of the contrastive loss. This loss function manipulates distances between pairs of data points that share similar distributions, compelling these distances to converge towards zero, while simultaneously driving apart the distances between data pairs manifesting dissimilar distributions, aiming to push these distances towards a specified margin (Fig. 2). By doing so, our model assimilates both the comprehensive data distribution and the nuanced data relationships, culminating in heightened accuracy relative to models reliant solely upon the cross-entropy loss (Table S1).

Training mechanism

To establish the validity of our methodology, we performed K-fold cross validation with 10 splits. The initial nine partitions were allocated for training the first-layer classifiers, while the remaining partition was reserved for validation purposes, serving as an unseen dataset. For each MLP networks, it is trained 3000 epochs with Adam optimizer. Meanwhile, the hyperparameters governing the metaclassifier were systematically refined through a grid search process. The overall training pipeline can be seen in Fig. 3.

Network interpretability

Even though deep learning models inherently possess an opaque nature, we harnessed the potential of SHAP (Shapley Additive exPlanation) values to elucidate the facets of patient attributes exerting influence upon the prediction outcomes. SHAP employs a game-theoretic framework to assess the contribution of each feature towards the prediction. This method assigns each feature an importance value for a particular prediction, allowing us to understand the contribution of each feature to the model's output. SHAP also offers several advantages, including consistency, local accuracy, and the ability to handle both linear and non-linear relationships within

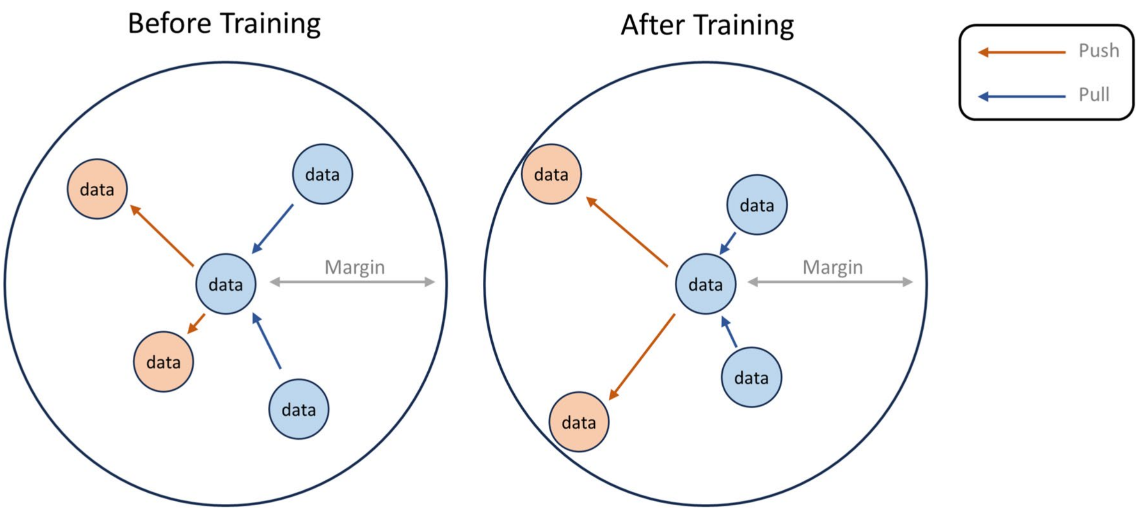

Figure 2. Mechanism of contrastive loss function showing distance manipulation between similar and dissimilar data point pairs.

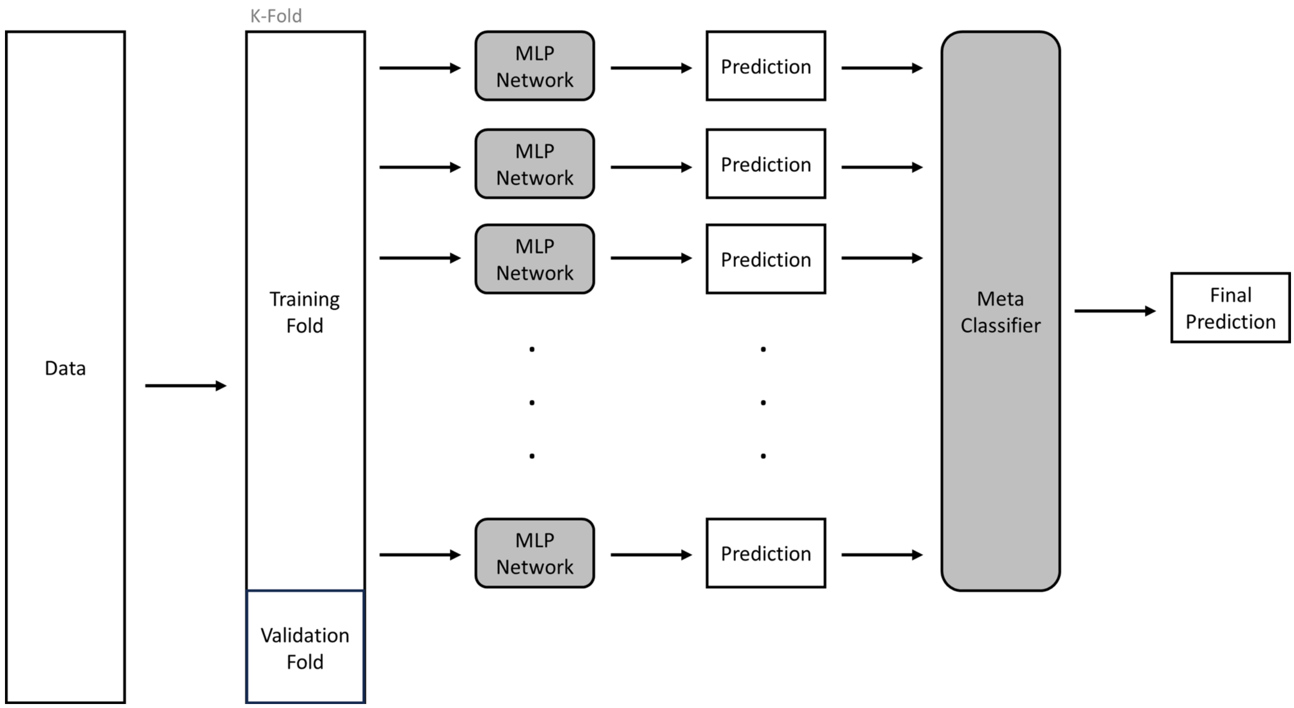

Figure 3. Overview of the training pipeline. *MLP*, Multilayer Perceptron.

the data[17]. Furthermore, since our network is comprised of two levels, we also evaluated the impact to the final prediction wielded by the output of each distinct MLP network.

Ethical consideration
Written informed consent was obtained from all patients. This investigation was approved by the Institutional Review Board (IRB) at the Hanyang University Guri Hospital and performed in accordance with the Declaration of Helsinki and Good Clinical Practice guidelines (IRB FILE No : 2023-08-004).

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Results
Clinical characteristics of study population
Of the 1108 SSNHL patients included in the study, 505 (45.6%) were male and 603 (54.4%) were female. The mean age of the patients was 54.4 ± 14.6 years. 506 (45.7%) patients had symptoms in the right ear and 602 (54.3%) in the left ear. Associated symptoms included dizziness in 307 (27.7%), tinnitus in 640 (57.8%), and ear fullness in 517 (46.7%). 307 (27.7%) patients had hypertension, 239 (21.6%) had diabetes, and 37 (3.3%) had a cardiovascular disease. The average time from symptom onset to treatment was 6.9 ± 24.5 days. At initial audiometric assessment, the mean pure tone threshold in the affected ear was 63.4 ± 27.8 dB, compared with 23.0 ± 18.9 dB in the unaffected ear. And, the initial WRS for the affected ear averaged 49.2 ± 38.8%, and for the unaffected ear, it was 93.9 ± 17.6%. According to Siegel's criteria, 352 (31.8%) patients achieved complete recovery, and the AAO-HNS classification indicated 438 (39.5%) patients as Class A. (Table 1).

Performance evaluation of deep learning models
The average accuracy of the first-layer classifiers based on Siegel's criteria was approximately 82.3%, while the AAO-HNS classification showed an average accuracy of around 76.3%. These values increased to 83.5% for Siegel's criteria and 80.8% for AAO-HNS classification when the meta-classifier was introduced. When trained without the constraints of the K-Fold strategy, the accuracy reached its peak; 89.2% for Siegel's criteria and 84.7% for AAO-HNS classification. (Table 2).

When we calculated the area under the curve (AUC) value from the receiver operating characteristic (ROC) curve, we found a value of 0.922 for Siegel's criteria (Fig. 4A) and 0.918 for AAO-HNS classification (Fig. 4B).

Predictive features for hearing recovery
The deep learning model identified several significant features instrumental in predicting hearing recovery. These results were evaluated by calculating individual SHAP values from both models and then averaging them to derive a combined ranking. Notably, the most significant predictor was the initial pure tone threshold at

Variables	Overall SSNHL N = 1108
Sex	
Male/Female	505 (45.6%) / 603 (54.4%)
Age	54.4 ± 14.6
Underlying disease	
Hypertension	307 (27.7%)
Diabetes mellitus	239 (21.6%)
Cardiovascular disease	37 (3.3%)
Affected side	
Right / Left	506 (45.7%) / 602 (54.3%)
Associated symptom	
Vertigo	307 (27.7%)
Tinnitus	640 (57.8%)
Ear fullness	517 (46.7%)
Onset of treatment (days)	6.9 ± 24.5
Initial hearing pure tone threshold (dB)	
Affected ear	63.4 ± 27.8
Unaffected ear	23.0 ± 18.9
Initial hearing word recognition score (%)	
Affected ear	49.2 ± 38.8
Unaffected ear	93.9 ± 17.6
Hearing gain (dB)	19.7 ± 23.0
Hearing recovery (Siegel's criteria)	
Complete recovery	352 (31.8%)
Partial recovery	131 (11.8%)
Slight recovery	97 (8.8%)
No recovery	528 (47.7%)
Hearing recovery (AAO-HNS classification)	
Class A	438 (39.5%)
Class B	268 (24.2%)
Class C	137 (12.4%)
Class D	265 (23.9%)

Table 1. Demographic and Clinical Characteristics of the Study Population. SSNHL, sudden sensorineural hearing loss; AAO-HNS, American Academy of Otolaryngology-Head and Neck Surgery.

4000 Hz on the affected side, followed by age, initial pure tone threshold at 2000 Hz on the unaffected side, and initial pure tone threshold at 2000 Hz on the affected side. The subsequent ranking in order of importance is as follows: presence of tinnitus, initial pure tone threshold at 4000 Hz on the unaffected side, initial pure tone threshold at 500 Hz on the affected side, initial WRS on the affected side, initial pure tone threshold at 1000 Hz on the unaffected side, presence of ear fullness, sex, initial pure tone threshold at 1000 Hz on the affected side, onset of treatment, affected side, presence of vertigo, hypertension, diabetes mellitus, initial pure tone threshold at 500 Hz on the unaffected side, initial WRS on the unaffected side, and finally, cardiovascular disease. (Table 3).

Online access

We have developed a website based on these deep learning models that allows clinicians to input variables and predict the probability of a patient's hearing recovery. Access to this tool is available through the following link: https://colab.research.google.com/drive/16YIIcgKEr-EE9Je3Wo3RpoIBirmeiIqR?usp=share_link. Through this platform, clinicians can assess the probability of a patient's prognosis with a rapid online calculation. (Fig. S1).

Discussion

Idiopathic SSNHL remains a complex otologic challenge, and prognosis prediction is crucial to formulate effective and personalized treatment strategies. In this study, we used a large dataset of 1108 SSNHL patients to construct a deep learning model for predicting hearing recovery. Our results showed promising accuracy across both Siegel's criteria and AAO-HNS classification. In particular, we found that the accuracy of the model was further improved when the constraints of the K-fold strategy were removed, highlighting the potential for optimizing the learning process in this way. Additionally, by discerning predictive factors that significantly influence hearing recovery, we have provided valuable insights into the prediction process. These findings demonstrate the potential of deep learning algorithms for prognosis prediction in SSNHL.

Criteria	MLP architecture	K-fold10 model Average accuracy	K-fold10 meta classifier Average accuracy	Meta classifier Top accuracy
Siegel's criteria (complete recovery)	Model_32_64_128_32	80	0.835	0.892
	Model_64_32_32_16_8	82.72727273		
	Model_64_64_32_16_8	81.81818182		
	Model_128_32_16_16_8	80.90909091		
	Model_128_32_32_16_8	80.90909091		
	Model_128_64_32	83.63636364		
	Model_128_64_32_16	80		
	Model_128_64_32_16_8	84.54545455		
	Model_128_64_32_32_8	86.36363636		
	Model_128_64_32_32_16	81.81818182		
	Model_128_64_64_16_8	80.90909091		
	Model_128_64_64_32_8	81.81818182		
	Model_128_64_64_32_16	81.81818182		
	Model_128_128_32_16_8	82.72727273		
	Model_128_128_64	82.72727273		
	Model_128_128_64_16_8	82.72727273		
	Model_128_128_64_32	82.72727273		
	Model_128_128_64_32_8	81.81818182		
	Model_128_128_64_32_16	80		
	Model_128_256_128	85.45454545		
	Model_128_256_128_64	84.54545455		
	Model_128_256_128_64_16	80		
	Average	82.27272727		
AAO-HNS classification (Class A)	Model_32_64_128_32	74.54545455	0.808	0.847
	Model_64_32_32_16_8	80		
	Model_64_64_32_16_8	79.09090909		
	Model_128_32_16_16_8	77.27272727		
	Model_128_32_32_16_8	78.18181818		
	Model_128_64_32	72.72727273		
	Model_128_64_32_16	77.27272727		
	Model_128_64_32_16_8	72.72727273		
	Model_128_64_32_32_8	74.54545455		
	Model_128_64_32_32_16	74.54545455		
	Model_128_64_64_16_8	76.36363636		
	Model_128_64_64_32_8	75.45454545		
	Model_128_64_64_32_16	78.18181818		
	Model_128_128_32_16_8	78.18181818		
	Model_128_128_64	79.09090909		
	Model_128_128_64_16_8	76.36363636		
	Model_128_128_64_32	74.54545455		
	Model_128_128_64_32_8	78.18181818		
	Model_128_128_64_32_16	74.54545455		
	Model_128_256_128	74.54545455		
	Model_128_256_128_64	73.63636364		
	Model_128_256_128_64_16	79.09090909		
	Average	76.32231405		

Table 2. Results of meta classifier. MLP, Multilayer Perceptron; AAO-HNS, American Academy of Otolaryngology-Head and Neck Surgery.

Previous predictive models primarily use statistical methodologies. Suzuki et al[18]. employed multiple regression analysis, revealing that age, days from onset to treatment, initial hearing level, and the presence of vertigo were significant prognostic factors for hearing recovery. Utilizing the regression coefficients of these factors, they formulated a linear equation to predict the outcome. Similarly, Chao et al[19]. performed multivariate analysis, identifying distortion product otoacoustic emission, auditory brainstem response, vestibular evoked myogenic potential, and audiometric types as significant predictors for hearing improvement. They subsequently utilized

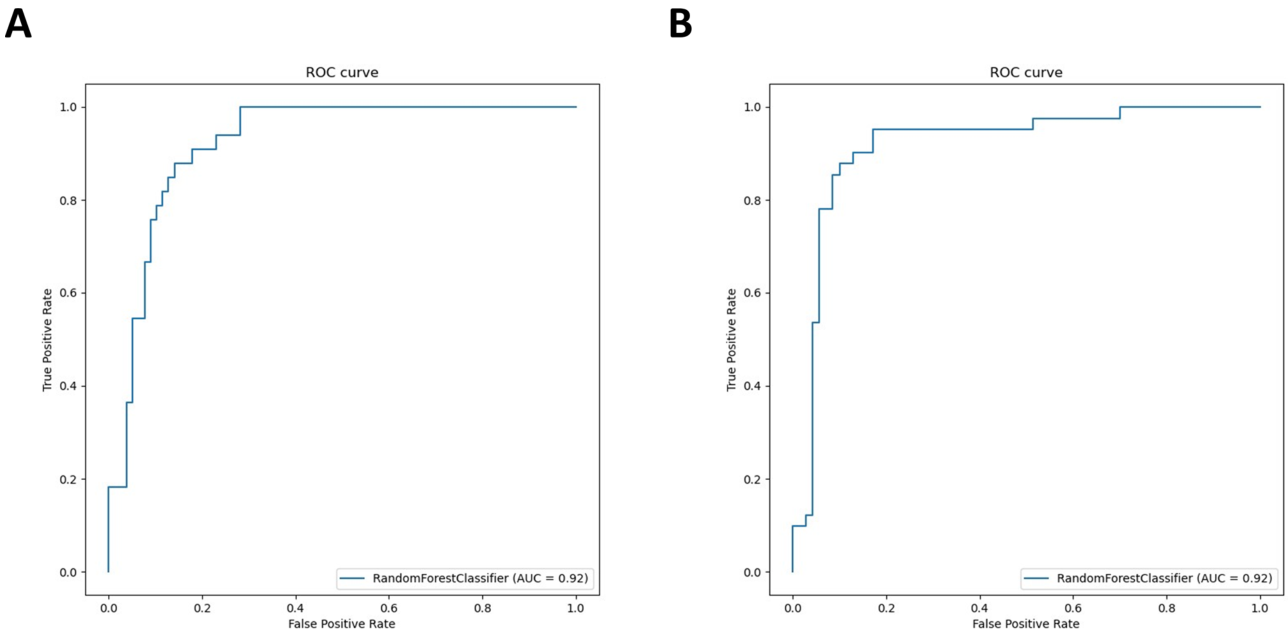

Figure 4. Receiver operating characteristic (ROC) curve according to (**A**) Siegel's criteria and (**B**) AAO-HNS classification.

Variables 20 parameters	SHAP value			Ranking
	Siegel's criteria	AAO-HNS classification	average	
Sex	0.008138	0.00753	0.007834	11
Age	0.015814	0.019799	0.017806	2
Hypertension	0.005469	0.005819	0.005644	16
Diabetes mellitus	0.004549	0.005548	0.005048	17
Cardiovascular disease	0.001008	0.001833	0.001421	20
Affected side	0.005283	0.007728	0.006505	14
Vertigo	0.005367	0.006515	0.005941	15
Tinnitus	0.008462	0.01227	0.010366	5
Ear fullness	0.007327	0.009304	0.008315	10
Onset of treatment (days)	0.007321	0.007051	0.007186	13
Initial hearing level (Affected side)				
Pure tone threshold, 500 Hz (dB)	0.007493	0.010173	0.008833	7
Pure tone threshold, 1000 Hz (dB)	0.006686	0.008798	0.007742	12
Pure tone threshold, 2000 Hz (dB)	0.01103	0.014276	0.012653	4
Pure tone threshold, 4000 Hz (dB)	0.035233	0.050677	0.042955	1
Word recognition score (%)	0.010224	0.00701	0.008617	8
Initial hearing level (Unaffected side)				
Pure tone threshold, 500 Hz (dB)	0.00431	0.00453	0.00442	18
Pure tone threshold, 1000 Hz (dB)	0.009615	0.007333	0.008474	9
Pure tone threshold, 2000 Hz (dB)	0.016547	0.015824	0.016185	3
Pure tone threshold, 4000 Hz (dB)	0.009862	0.009819	0.009841	6
Word recognition score (%)	0.002769	0.003864	0.003317	19

Table 3. Variables and SHAP value. SHAP, Shapley Additive exPlanation, AAO-HNS, American Academy of Otolaryngology-Head and Neck Surgery.

the Bayesian cure rate model to predict both the probability of recovery and the time to improvement. As such, while multivariate analyses can easily identify the various factors influencing prediction, it fundamentally operates on the concept of linear equations, lacking the ability to understand complex interactions between variables.

Artificial intelligence (AI) is gaining popularity in healthcare due to its ability to understand complex interactions between variables and adapt to new information. Recently, AI has been extensively used in various medical fields, mainly in image diagnosis and prognosis prediction. To date, several models using AI to predict the prognosis of SSNHL have been introduced. Bing et al[20]. developed a deep belief network model using 149 variables in a cohort of 1220 patients, achieving an accuracy of 77.58%. These 149 variables included demographics as well as medical records, medications, pure tone audiometry, and laboratory test results. However, due to the large number of variables, it can be difficult to obtain such comprehensive data from every patient in a clinical setting. In a study of 453 patients, Lee et al[21]. developed a machine learning model that incorporated 38 variables, including vestibular function test results and laboratory findings, and reported an accuracy of 75.36%. Similarly, the inclusion of vestibular function tests and laboratory findings, which are not routinely performed on all patients with SSNHL, may not be readily applicable in a clinical setting. In this context, the strength of our study is that we developed a model that can easily assess prognosis based on information available only from the initial consultation and audiological assessment.

In other models, Park et al[22]. devised a prognosis prediction model for 227 patients, achieving an accuracy of 75.4%. Uhm et al[10]. model, involving 298 patients, showed an accuracy of 88.8%, while Lin et al[23]. demonstrated 92.1% accuracy with a cohort of just 64 patients. However, considering that AI models tend to better generalize and capture inherent patterns with increased data, the aforementioned studies are limited by their smaller sample sizes. The top accuracy achieved in this study was 89.2% based on Siegel's criteria and 84.7% based on AAO-HNS classification, which is comparable to other studies. Considering that our study was based on a relatively large patient cohort of 1108 patients, it provides high reliability for the model accuracy.

One of the notable findings of this study was the identification of significant predictors of hearing recovery through individual SHAP values. The results showed that the initial pure tone threshold at 4000 Hz on the affected side was the most significant predictor, which is consistent with previous research showing that hearing loss of descending configuration, manifested as high frequency hearing loss, is an unfavorable prognostic factor[5,7,24]. In addition, age, another significant predictor, has consistently been recognized in the literature as influencing hearing recovery[7,24,25].

Interestingly, hearing threshold on the unaffected side was identified as a significant predictor in this study. While Uhm et al[10]. previously highlighted the crucial role of initial hearing threshold at 250 Hz in the non-affected ear for predicting hearing recovery, other studies have not recognized the hearing threshold of the unaffected ear as a prognostic predictor. In our study, an initial pure tone threshold at 2000 Hz on the unaffected side had the third highest impact on hearing recovery, and an initial pure tone threshold at 4000 Hz on the unaffected side had the sixth highest impact. This study suggests that, similar to Uhm's findings, hearing on the unaffected side is also important in predicting hearing recovery, and has significant prognostic value, especially at higher frequencies. It is not known why only certain frequencies in the unaffected ear had a prognostic impact, but it is thought that other unmeasured variables such as audiograms may have played a role. A more comprehensive analysis of audiogram profiles across all frequencies may be needed to fully understand these differences.

Two interpretations can be drawn as to why contralateral hearing affects prognosis. First, SSNHL patients who also had previously poor hearing in the unaffected side may have experienced difficulties in their hearing recovery because their overall auditory system was poorer due to the complex interaction between the auditory mechanisms in both ears. For the second interpretation, it is important to recognize that an individual's baseline hearing may be different, so Siegel's criteria of "complete recovery" may not be universally applicable. Because most individuals have symmetrical hearing before the onset of SSNHL, initial pure tone threshold on the unaffected side could act as a reference to predict the baseline hearing of the affected side. In individuals with higher baseline hearing thresholds, even if their hearing improves to match the contralateral side, it might still not fall within the 25 dB threshold for "complete recovery" in Siegel's criteria, and under strict criteria this could be classified as non-recovery. Such interpretations suggest that the widely used Siegel's criteria might not be appropriate for individuals with pre-existing hearing loss, and highlights the limitations of conventional criteria.

According to the AAO-HNS's 2019 clinical practice guideline for sudden hearing loss[1], a new guideline was proposed to assess hearing recovery based on hearing in the contralateral ear due to the limitation of unknown pre-onset hearing level in the affected ear. However, this outcome assessment method was designed for patients without pre-existing hearing asymmetry. In the present study, we were unable to use this guideline because we couldn't assess all patients for pre-existing hearing asymmetry due to the limitations of retrospective chart review. It is possible that some patients had pre-existing hearing asymmetry before the onset of SSNHL, highlighting the need for a universally applicable outcome assessment guideline in the future.

Our deep learning model also emphasized lesser-known predictors, such as tinnitus or ear fullness, over well-known predictors such as time to treatment onset or the presence of vertigo[6,7]. This suggests that even previously underestimated patient-reported symptoms can provide valuable insights into hearing recovery prognosis when analyzed using deep learning methodologies. We expect that collecting more data and retraining and updating the model in the future will allow us to further understand the impact of these variables.

While this study presents a promising deep learning model for predicting hearing recovery in patients with SSNHL, there are some limitations. Firstly, the retrospective design limited the number of variables available. Secondly, although the sample size was relatively large compared to other studies, it was still not sufficient for optimal AI training. Additionally, due to the unique characteristics of medical research data, a two-layer classification system utilizing MLP networks and meta-classifier was employed instead of a larger single neural network. This choice was informed by our dataset's complexity and the need to manage intricate data relationships effectively. Medical datasets often face challenges in acquiring large amounts of real patient data, particularly negative samples, which are important but often less available for balanced model training. In addition, it is frequently unclear in medical data which features are most predictive of outcomes, so we needed an architecture that can maximize data utility despite these limitations. In future research, we aim to apply this model to larger datasets, which will allow for an even more comprehensive analysis and potentially enable the integration of a simplified, more efficient neural network architecture. Finally, we did not predict the final hearing threshold for individual patients, as we simply categorized hearing recovery into "complete recovery" and "Class A". In future research, if a deep learning model is developed by integrating a larger patient cohort, it is anticipated that these prediction models can contribute effectively to providing better patient counseling for patients with SSNHL.

Conclusion

Using data from 1108 SSNHL patients, we developed a deep learning model to predict hearing recovery with high accuracy, suggesting its usefulness for personalized patient counseling. Future model refinements and larger data sets are expected to increase its clinical relevance.

Data availability

Anonymized data analyzed during this study are available from the corresponding author on reasonable request.

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J.H.C and T.H.K had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. Conceptualization: H.W.S, Y.J.O, S.H.L, J.H.C, T.H.K; Data curation: J.O, D.K.L; Formal analysis: Y.J.O, T.H.K; Funding acquisition: J.H.C; Investigation: J.O, D.K.L; Methodology: Y.J.O, T.H.K; Project administration: J.H.C, T.H.K; Resources: H.W.S, J.H.C; Supervision: S.H.L, J.H.C, T.H.K; Validation: J.O, D.K.L; Visualization: H.W.S, Y.J.O; Roles/Writing—original draft: H.W.S, Y.J.O; Writing—review & editing: S.H.L, J.H.C, T.H.K.

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