

Deep Learning Detection of Facial Nerve Enhancement in Bell's Palsy

Habip Eser Akkaya, Önder Polat¹, Nur Hürsoy², Dorukan İnanç Akpınar

Department of Radiology, Ankara Training and Research Hospital, Ankara, Türkiye, ¹Department of Electrical and Electronics Engineering, Gaziantep İslam Science and Technology University, Gaziantep, Türkiye, ²Department of Radiology, Recep Tayyip Erdoğan University, Rize, Türkiye

Abstract

Background and Objectives: The facial nerve, or seventh cranial nerve, with its complex course and association with multiple pathologies, remains a critical area of study. Bell's palsy, an idiopathic condition leading to unilateral facial weakness, is frequently diagnosed through magnetic resonance imaging (MRI), which can reveal inflammation or pathology within the facial nerve. However, physiological enhancement can complicate diagnosis, particularly in healthy individuals. This study aimed to assess facial nerve enhancement in Bell's palsy patients using machine learning algorithms. **Methods:** We retrospectively analyzed 306 MR images from subjects, including 156 Bell's palsy patients and 150 controls, and trained a DenseNet-based deep learning model to identify pathological enhancement with an 80% accuracy (area under the curve (AUC) 87%). **Results:** Our model achieved an accuracy of 80% and an AUC of 87% as compared to neuroradiologist's decision, demonstrating its potential to aid clinicians in diagnosis. **Conclusions:** Future studies with external validation and larger datasets may further enhance the clinical applicability of AI-based assessment tools for facial nerve pathologies.

Keywords: Facial nerve, Bell's palsy, machine learning, MRI, pathological enhancement, DenseNet, artificial intelligence, cranial neuropathy

Introduction

The facial nerve, seventh cranial nerve, has a complex anatomical course and is associated with a wide range of clinical conditions.^[1] Scientific interest in the facial nerve remains high, with numerous recent publications addressing its anatomy, examination methods, and related pathologies.^[2] Among cranial neuropathies, seventh nerve involvement is the most common,^[3] and Bell's palsy is the leading cause of unilateral facial paralysis, significantly affecting quality of life.^[4] Historical descriptions date back centuries,^[5-8] yet its etiology remains incompletely understood, with inflammation, ischemia, viral infection, and anatomical factors all proposed.^[4]

Although Bell's palsy is primarily a clinical diagnosis, contrast-enhanced magnetic resonance imaging (MRI) is the only objective marker, allowing visualization of asymmetric enhancement along the facial nerve and enabling exclusion of alternative temporal bone pathologies.^[9] However, physiological enhancement normally occurs in several segments—including the geniculate ganglion, tympanic, and mastoid regions—which complicates interpretation.^[10] Distinguishing pathological from physiological enhancement therefore remains a major diagnostic challenge.

Recent imaging studies have characterized MRI findings in Bell's palsy,^[3] and artificial intelligence (AI) applications in cranial nerve imaging have focused on segmentation or functional imaging tasks.^[11,12] Yet, no study to date has evaluated facial nerve enhancement in Bell's palsy using machine learning algorithms, despite the persistent difficulty of identifying abnormal enhancement.^[13] AI-assisted analysis

may help radiologists resolve this diagnostic dilemma by highlighting subtle asymmetric patterns and prioritizing potentially abnormal scans.^[14]

Despite advances in MRI techniques, differentiating pathological facial nerve enhancement from physiological enhancement remains a major diagnostic challenge, even for experienced radiologists. Physiological enhancement is frequently observed in healthy individuals, particularly in the geniculate, tympanic, and mastoid segments, leading to potential diagnostic ambiguity. Although artificial intelligence applications have been increasingly explored in cranial nerve imaging, existing studies have focused primarily on segmentation or functional assessment rather than enhancement pattern differentiation. To our knowledge, no prior study has applied machine learning algorithms specifically to distinguish pathological facial nerve enhancement associated with Bell's palsy from physiological

Address for correspondence: Dr. Habip Eser Akkaya, Hacettepe, Ulucanlar Cd. No: 89, 06230 Altındağ, Ankara. E-mail: habipeser.akkaya@saglik.gov.tr

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enhancement. Addressing this unmet need, the present study investigates the feasibility of a deep learning-based approach to assist radiologists in differentiating pathological enhancement in Bell's palsy from normal variants.

Methods

The present study has a retrospective cohort design. This study was approved by the Clinical Research Ethics Committee of Ankara Education and Research Hospital (Date: 2023-09-06, No: E 23-1358). Temporal MR images (1.5 T; Siemens Aera, Erlangen, Germany) collected between January 2018 and May 2023 were compiled and listed. The study included 159 patients with pathological facial nerve enhancement on temporal MRI who were diagnosed with Bell's palsy during follow-up. The control group comprised 150 patients, matched to the case group in terms of age and sex, who underwent temporal MRI for other indications, such as cholesteatoma, trigeminal neuralgia, or tinnitus, and who showed no pathological facial nerve enhancement or diagnosis of Bell's palsy during follow-up. Of the total 309 patients, three were excluded due to non-diagnostic image quality. All temporal MR images were evaluated for pathological enhancement of the facial nerve by two radiologists—one of whom was a neuroradiologist—with more than 10 years of experience, using a final consensus approach. To assess inter-rater reliability, a randomized 10% subsample of the entire dataset was independently reviewed by the two researchers. In this subsample, the kappa score was determined to be 0.88.

Patient gender, age, diagnosis of Bell's palsy, presence of enhancement, laterality of enhancement, and the segment showing enhancement were recorded. When enhancement was present in multiple segments, this was noted and grouped accordingly. Patients with marked, asymmetric linear intensity increase in the facial nerve tract on post-contrast series, compared to pre-contrast images, were considered positive. Bilateral, subtle intensity increases were regarded as normal. Subtle enhancement is described as minimal intensity increase on post-contrast sequences. Pathological enhancement was classified as either present or absent, with no grading applied. Patients with pathological contrast enhancement of the facial nerve were included in the patient group, and those without were included in the control group. A grading system for facial nerve contrast enhancement was not preferred as it was deemed impractical and potentially complicating to algorithm development.

For deep learning, normalization and resizing were applied to the images. Initially, pixel values were preprocessed to have zero mean and unit variance for normalization. This process aids in balanced weight updates, accelerates the model's optimization process, and improves the efficiency of activation functions. Additionally, each slice was resized to 96×96 pixels. These steps ensure that the images are standardized in size with scaled pixel values, aiming for more efficient processor and memory usage. Prior to inputting the images

Table 1: Frequency of enhanced segment/segment groups in the facial nerve

The enhanced segment or segments	n=156
Canalicular segment	77 (49.4%)
Labyrinthine segment	17 (10.9%)
Canalicular and labyrinthine segments	35 (22.4%)
Canalicular, labyrinthine, and geniculate segments	7 (4.5%)
Labyrinthine, geniculate, tympanic, and mastoid segments	1 (0.6%)
Labyrinthine and geniculate segments	5 (3.2%)
Canalicular, labyrinthine, geniculate, tympanic, and mastoid segments	14 (9%)

All values are presented as number (%)

into the model, a cropping procedure was applied to focus on the region containing the facial nerve. This cropping was adjusted based on dataset review to capture the largest possible area without data loss.

To develop and evaluate our DenseNet-based deep learning model, the 306 MRI examinations were divided into three subsets: training (70%), validation (10%), and testing (20%). This 70-10-20 split, a standard approach in machine learning, was chosen to balance the need for sufficient training data with robust validation and unbiased testing, particularly in the context of deep learning for MRI-based disease prediction such as Bell's palsy. The primary rationale for this split is its integration with 5-fold cross-validation (CV), described in detail in the CV section, where the dataset is initially partitioned into 80% for training/validation and 20% for testing, with the 80% further divided into 70% for training and 10% for validation to support hyperparameter tuning and model selection, a step particularly relevant for deep learning models. The training set was used to teach the model to recognize positive cases by analyzing a large portion of the data, allowing it to learn complex patterns in Bell's palsy. The validation set was used during training to monitor the model's performance and prevent overfitting, ensuring it could generalize to new data. The testing set was reserved for final evaluation, providing an unbiased assessment of the model's accuracy and area under the curve (AUC) on unseen images. The 70-10-20 split is commonly used in deep learning studies, as evidenced by its application in detecting brain abnormalities in MRI scans,^[15] classifying proximal femur fractures,^[16] and developing an ECG-based model for cirrhosis prediction.^[17] While the 70-10-20 split is a standard and widely adopted approach, we acknowledge that other splits, such as 80-10-10 or 60-20-20, are also employed depending on dataset size and study requirements. The split was performed randomly but stratified to maintain a balanced representation of positive and negative cases.

The deep learning model used was the DenseNet^[18] architecture with 264 layers. DenseNet is an efficient deep learning architecture that establishes dense connections between layers, allowing each layer to receive information directly from all previous layers. This structure enhances information flow while optimizing the number of parameters.

DenseNet's advantage lies in minimizing data loss and enabling efficient gradient flow, thus accelerating the learning process.

For this study, the DenseNet architecture was applied to 3-dimensional (3D) medical imaging data. A 3D convolutional neural network (CNN) was employed to effectively capture information across each axis, allowing deeper structural features to be learned. This approach aims to improve the model's ability to understand the complex structural characteristics of medical images, thereby achieving higher accuracy rates. The structure of the deep learning-based system developed in this study is illustrated in Figure 1.

Model training was conducted using Python language and the PyTorch library. This process utilized a system equipped with an AMD Ryzen-5 processor, 16 GB Random Access Memory (RAM), and an Nvidia RTX 3060 graphics card with 6 GB Video RAM. Test data were withheld during training, with the model exposed only to the training and validation datasets. An early stopping technique was employed to terminate the training process once the model could no longer improve, ensuring that the best-performing model up to that point was saved. Without early stopping, the maximum number of iterations was set to 100. The batch size was set at 8 per iteration, and the learning rate was optimized to 3×10^{-4} , ensuring both time and energy efficiency.

The sample size in this study was determined by the number of eligible patients identified retrospectively from our institutional database. No formal sample size calculation was performed. To mitigate the effects of limited data, we used 5-fold CV to evaluate model performance and ensure generalizability.

5-Fold CV process

To ensure robust evaluation of our DenseNet model, we employed 5-fold CV. The 306 MRI examinations were randomly divided into five equal folds (roughly 61 images

each), with stratification to maintain balanced representation of positive and negative cases. In each of the five iterations, one fold was used as the testing set, and the remaining four folds were split into training and validation sets. The model was trained from scratch in each iteration, fine-tuned using the validation set to prevent overfitting, and evaluated on the testing set. Performance metrics (accuracy, sensitivity, specificity, and AUC) were calculated for each fold's testing set, and the averages, along with standard deviations, are reported in Table 2. This approach, akin to testing a diagnostic tool across multiple patient cohorts, ensures that the model's performance is reliable and generalizable to new MRI scans, enhancing its potential as a clinical support tool for detecting facial nerve enhancement in Bell's palsy.

Overview of the machine learning approach

To ensure that our methodology is understandable to clinicians, we provide a simplified overview of how the machine learning system was developed and evaluated. Our approach used a 3D DenseNet model, a type of deep learning algorithm that learns to identify patterns across MRI slices. In this study, the dataset was labeled by experienced radiologists who identified cases consistent with Bell's palsy based on MRI findings. These expert-labeled cases served as the ground truth for training and evaluating the deep learning model. We used a 3D DenseNet architecture, a type of CNN capable of analyzing spatial patterns across consecutive MRI slices. Our model was trained to distinguish these patterns by processing MRI images, similar to how radiologists visually inspect scans but with automated pattern recognition.

The algorithm was trained using a standard machine learning workflow: (1) input MR images were preprocessed (resized, normalized, and cropped to focus on the facial nerve), (2) the dataset was split into training, validation, and test sets, and (3) the model was iteratively optimized to reduce error on the training set, while using validation data to prevent overfitting. Model performance was measured using accuracy, sensitivity, specificity, and area under the receiver operating

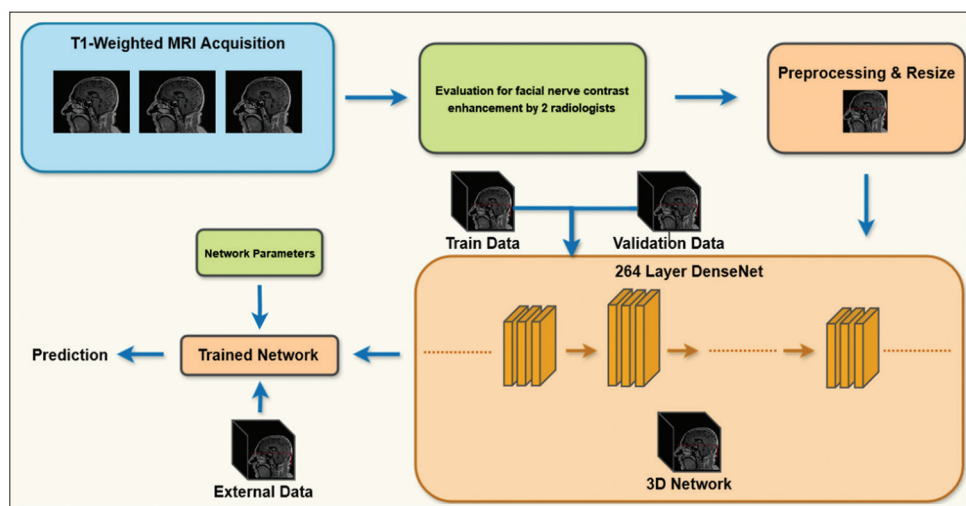


Figure 1: Structure of the deep learning based prediction system. MRI: Magnetic resonance imaging

Table 2: Performance results for the trained model (average of 5-fold CV)

Metric	Value (%)	Standard Deviation (%)	Confidence Interval (95%)
Accuracy	80.46	3.04	77.79–83.12
Sensitivity	78.29	6.78	72.34–84.23
Specificity	82.67	5.48	77.87–87.47
AUC	87.30	2.90	84.76–89.84

AUC: Area under the curve, CV: Cross-validation

characteristic (ROC) curve (AUC)—metrics familiar to clinicians from diagnostic test evaluation.

In summary, our model identifies contrast enhancement patterns and classifies them based on prior examples. This makes it a potentially valuable decision-support tool for clinicians unfamiliar with the subtle nuances of facial nerve enhancement on MRI. Its performance was evaluated using commonly understood diagnostic metrics such as accuracy, sensitivity, specificity, and AUC.

The methodological steps followed in this study are illustrated in the flowchart [Figure 2].

Statistical analysis

Statistical analysis of the study was performed using the Statistical Package for Social Sciences (SPSS) Version 21.0 (SPSS Inc., Chicago, IL, USA). Descriptive analyses were performed using mean and standard deviations. Categorical variables are given as numbers and percentages.

Results

Among the patients included in the study, 162 were females and 144 were males, with a mean age of 50.96 ± 16.14 years. There were 156 patients diagnosed with Bell's palsy who had pathological enhancement in the facial nerve. No significant differences in age or gender were found between patients with pathological facial nerve enhancement and those without ($P = 0.77$ and 0.21 , respectively). The enhanced segments and their frequencies are presented in Table 1. Figure 3 shows an example of pathological facial nerve enhancement. No enhancement was observed in the extracranial or cisternal segments. Additionally, no other pathologies were identified along the facial nerve tract in conventional sequences.

The performance of the trained model was evaluated using the test data. Performance metrics included accuracy, sensitivity, specificity, the ROC curve, and the AUC score. Table 2 summarizes the average performance metrics of the DenseNet model across the five folds of CV, providing a reliable estimate of its ability to detect pathological facial nerve enhancement. The model achieved an average accuracy of $80.46\% (\pm 3.04\%)$, correctly classifying 80% of MRI scans as having or not having facial nerve enhancement in Bell's palsy. Sensitivity ($78.29\% \pm 6.78\%$) indicates the model's ability to detect true Bell's palsy cases with enhancement, while specificity ($82.67\% \pm 5.48\%$) reflects its accuracy in identifying negative cases.

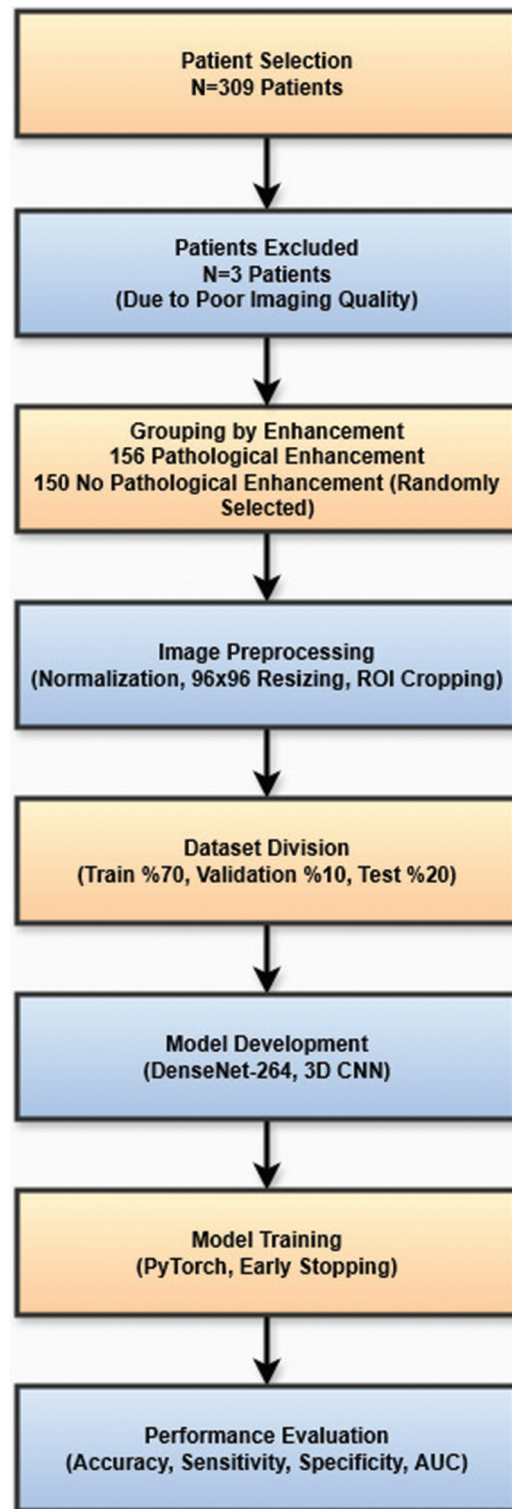


Figure 2: The methodological steps followed in this study are illustrated in the flowchart

The AUC ($87.30\% \pm 2.90\%$, 95% confidence interval (CI): $84.76\text{--}89.84\%$) demonstrates strong discriminative ability. The standard deviations show the consistency of these metrics across folds, with lower values indicating stable performance. The confusion matrix, averaged across the five folds, which summarizes the model's predictions: true positives (correctly

identified positives), true negatives (correctly identified negatives), false positives (incorrectly identified as positive), and false negatives (missed positive cases). For clinicians, this matrix is like a diagnostic test summary, showing that the model correctly identifies most cases (high True Positive [TP] and True Negative [TN]) while minimizing errors (low False Positive [FP] and False Negative [FN]), supporting its utility in assisting radiologists and practitioners in Bell's palsy diagnosis. The model predicted, on average, 24.6 samples as TP, 24.8 samples as TN, 5.2 samples as FP, and 6.8 samples as FN [Supplementary Figure 1]. Supplementary Figure 2 shows two example images; one true positive and one false negative sample based on the model's prediction.

Figure 4 displays the ROC curve, which evaluates the DenseNet model's ability to distinguish positive and negative cases across the five folds of CV. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) at various probability thresholds. For each test image in the five folds, the model outputs a probability score (0 to 1) indicating the likelihood of pathological enhancement. These probabilities were averaged across the five folds to generate the ROC curve, ensuring a robust performance measure. The AUC of 87.30% ($\pm 2.90\%$, 95% CI: 84.76–89.84%), reported in Table 2, indicates strong discriminative ability, comparable to a reliable diagnostic test. For clinicians, this means the model can accurately identify Bell's palsy cases with enhancement while minimizing false positives, supporting rapid and confident diagnosis in clinical practice.

Discussion

Idiopathic facial nerve paralysis, also known as Bell's palsy, is the most common cause of unilateral facial weakness. It occurs equally in males and females, particularly among individuals aged 15–45 years.^[19] Electrophysiological studies, used in diagnosis can be challenging to access. MRI, on the other hand, is preferred due to its accessibility, ability to

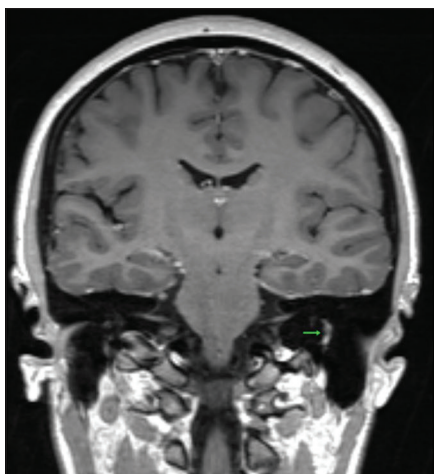


Figure 3: The enhanced facial nerve is seen in the area marked by the arrow on the coronal reformatted image of thin-slice contrast-enhanced T1-weighted MRI. MRI: Magnetic resonance imaging

reveal early findings, and capability to detect inflammation in the facial nerve as well as malignancy. However, there are differing opinions on whether enhancement is related to disease severity.^[3,20] Yücel et al.^[20] reported that no significant differences in contrast enhancement were observed between primary attacks and recurrences. When compared with their findings, our study similarly identified the canalicular and labyrinthine segments as the most frequently enhanced regions. This consistency suggests that these segments are particularly vulnerable in facial nerve involvement, although methodological differences between the two studies may account for minor variations.

In healthy individuals, facial nerve enhancement may be observed, particularly in the geniculate ganglion, tympanic, and mastoid segments. This finding has been suggested to arise from the peri-venous plexus surrounding the nerve within the fallopian canal.^[10,21] In our study, subtle bilateral intensity increases in the defined regions on post-contrast series were not considered pathological enhancement. However, unilateral prominent enhancement in the canalicular and labyrinthine segments was evaluated as pathological.

In their study, Hong and colleagues reported detecting enhancement on MR images in individuals with clinically normal facial nerve function. This enhancement, observed as a minimal signal increase, may result from flow slowing. In pathological enhancement, however, a marked signal increase is observed in multiple sections and adjacent to the vascular lumen.^[22]

Qin et al.^[23] demonstrated that, in addition to contrast enhancement, diffusion tensor MRI can also reveal nerve involvement in facial paralysis. Although new imaging techniques provide detailed information, atypical signal

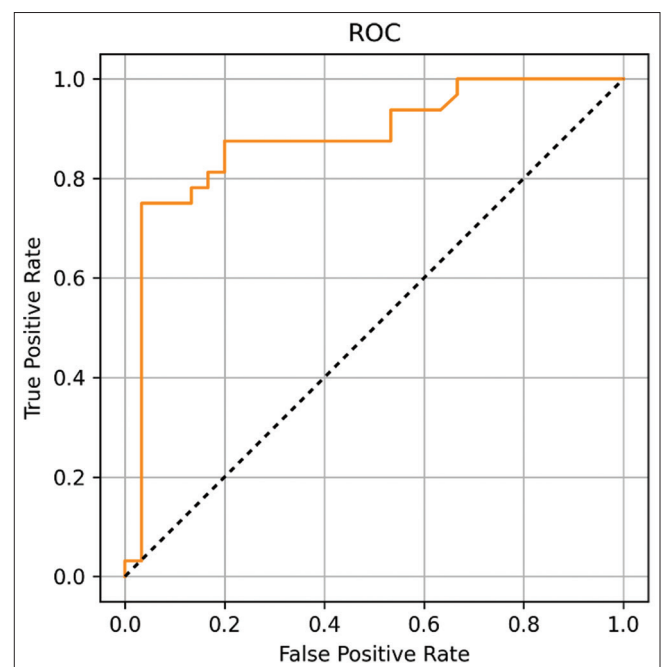


Figure 4: ROC curve from the average probability values. ROC: Receiver operating characteristic

characteristics can be detected, particularly in 3D MRI techniques. Therefore, it is important for radiologists to establish the “normal” range specific to each technique.^[24] Another advantage of MRI is its ability to reveal underlying pathologies involved in the etiology of facial paralysis. In a study compiling the findings of patients who underwent MRI with a preliminary diagnosis of Bell's palsy, brain lymphoma ($n = 2$), multiple sclerosis ($n = 2$), sarcoidosis ($n = 1$), and benign tumors ($n = 3$) were identified.^[9]

Studies utilizing artificial intelligence methods to elucidate cranial nerve pathologies include applications such as segmentation, correlating clinical findings with MR images and justifying the need for MRI.^[11,12,25] Our study is the first to investigate facial nerve enhancement using machine learning algorithms. Facial nerve enhancement, which can also be observed in healthy individuals, may pose challenges in diagnosis.^[10] In our study, we demonstrated that machine learning algorithms can distinguish facial nerve enhancement with high accuracy. Despite including cases with non-pathological facial nerve enhancement, the accuracy for identifying pathological enhancement reached 80%. The model's AUC value, achieving a high rate of 87%, is also promising. This indicates that our model has developed discriminative capabilities in detecting facial nerve enhancement and suggests that this rate could be further improved in future studies with new techniques.

Our DenseNet model, an artificial intelligence algorithm capable of detecting pathological enhancement of the facial nerve, can serve as a valuable “second opinion” tool, particularly for radiologists with limited experience in neuroradiology. In high-volume clinical settings, these algorithms can help prioritize cases with detected pathological enhancement, thereby accelerating diagnosis. Additionally, AI algorithms may serve as an effective adjunctive tool for training and education during specialist development.

This study has several limitations. First, the lack of external validation using data from other institutions may limit the generalizability of the proposed model, and multicenter external datasets are required to confirm its robustness and clinical applicability. Second, clinical outcomes such as recovery rates, treatment response, or disease severity were not correlated with model predictions, limiting assessment of the algorithm's prognostic or therapeutic relevance. Finally, subgroup analyses based on specific facial nerve enhancement segments were not performed and may provide additional insight into misclassification patterns in future studies.

Conclusions

In conclusion, this study demonstrates that a deep learning-based approach can identify pathological facial nerve enhancement in Bell's palsy with promising accuracy. While further validation and methodological refinements are required, the proposed model may serve as a supportive tool to assist radiologists and clinicians in the assessment of facial

nerve enhancement on MRI, particularly in challenging or high-volume clinical settings.

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Author contributions

HEA: conceptualization; methodology; data collection; data analysis; writing and editing. ÖP: conceptualization; data analysis; writing and editing. NH: conceptualization; data analysis; writing and editing. DİA: conceptualization; data collection.

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Nil.

Conflicts of interest

There are no conflicts of interest.

Data availability statement

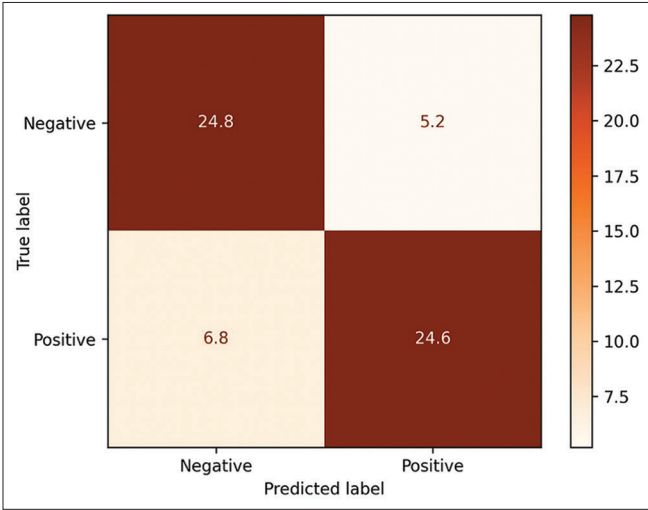
The data supporting the findings of this study are available upon reasonable request.

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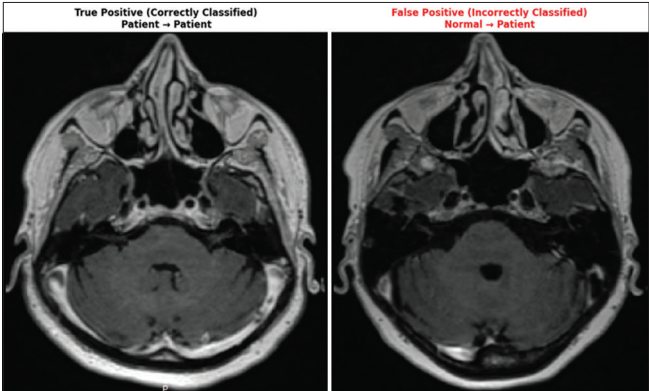
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Supplemantary Figures



Supplementary Figure 1: Confusion matrix for the trained model (average of 5 fold CV). CV: Cross validation



Supplementary Figure 2: The enhanced facial nerve is seen in the area marked by the arrow on the coronal reformatted image of thin slice contrast enhanced T1 weighted MRI. MRI: Magnetic resonance imaging