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PREDICTION OF VESTIBULAR SCHWANNOMA GROWTH BASED ON RADIOMICS FEATURES OF MRI IMAGES USING ENSEMBLE MACHINE LEARNING METHODS

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Abstract*—This paper proposes a method for predicting vestibular schwannoma growth based on the analysis of a single MRI scan using radiomics features and ensemble machine learning methods. A total of 96 patients from the public Vestibular-Schwannoma-MC-RC2 dataset were studied. 744 texture features were extracted using wavelet decomposition. A Voting ensemble combining five classifiers was proposed: SVM, logistic regression, k-NN, Random Forest, and LDA. ROC AUC of 0.742 ± 0.072 was achieved using 5-fold cross-validation. The results confirm the effectiveness of the proposed approach for early prediction of tumor growth.*

Keywords—Vestibular schwannoma; radiomics features; machine learning; ensemble methods; wavelet decomposition; tumor growth prediction.

I. INTRODUCTION

Choosing a treatment strategy for patients with vestibular schwannoma remains a complex clinical task. This benign tumor of the vestibulocochlear nerve is characterized by an unpredictable course: some neoplasms remain stable for years, while others demonstrate aggressive growth requiring surgical intervention [1], [4]. The current "wait-and-scan" strategy involves regular MRI examinations over months or years to detect growth dynamics [5]. However, this approach is resource-intensive, especially considering the increasing incidence of vestibular schwannoma [2], [3].

The relevant question is: can the future behavior of a tumor be predicted based on the analysis of a single MRI scan? A positive answer would allow optimizing the frequency of follow-up for low-risk patients and ensuring early intervention for high-risk patients.

Radiomics analysis opens new possibilities for solving this problem. Unlike traditional visual assessment, which is limited to tumor size and localization, the radiomics approach enables quantitative characterization of the internal structure of the neoplasm through hundreds of texture features [7]. These features reflect the microstructural heterogeneity of the tissue, which may correlate with the biological aggressiveness of the tumor [8].

Previous studies have demonstrated the potential of radiomics for predicting vestibular schwannoma growth, however, most studies used individual classifiers [22], [23]. Ensemble methods that combine predictions of several models can improve the stability and accuracy of prediction, especially on small samples [19]. The aim of this study is to develop and validate an ensemble method for predicting vestibular schwannoma growth based on wavelet-transformed radiomics features from a single MRI scan.

II. LITERATURE REVIEW

The concept of radiomics was proposed by Lambin et al. in 2012 and involves high-throughput extraction of quantitative features from medical images [7]. Radiomics features are divided into several categories.

- Shape features – describe geometric characteristics of the tumor: volume, surface area, sphericity, compactness [9].
- First-order features – statistical characteristics of voxel intensity distribution: mean, median, standard deviation, entropy [10].
- Texture features – describe spatial relationships between intensities of neighboring voxels. The main texture matrices include:

GLCM (Gray Level Co-occurrence Matrix) – gray level co-occurrence matrix [11], GLRLM (Gray Level Run Length Matrix) – run length matrix [12], GLSZM (Gray Level Size Zone Matrix) – size zone matrix [13], GLDM (Gray Level Dependence Matrix) – gray level dependence matrix [14],

NGTDM (Neighboring Gray Tone Difference Matrix) – neighboring tone difference matrix [15].

Wavelet transform allows analyzing images at different scales and frequencies [16]. Three-dimensional wavelet decomposition decomposes the image into 8 components: LLL, LLH, LHL, LHH, HLL, HLH, HHL, HHH, where L (low) – low-frequency component, H (high) – high-frequency component [17].

Application of wavelet filters before radiomics feature extraction allows detecting texture patterns at different scales, which increases the diagnostic value of features [18].

Ensemble machine learning methods demonstrate high effectiveness in medical diagnostics by combining predictions of several models [19]. The Voting method is one of the simplest and most stable ensemble approaches, especially on small samples [20].

Research on radiomics of vestibular schwannoma is a relatively new direction. The study used the public Vestibular-Schwannoma-MC-RC2 dataset from The Cancer Imaging Archive (TCIA) [21]. The dataset contains longitudinal MRI scans of patients with unilateral vestibular schwannoma from King's College Hospital, London, UK.

Inclusion criteria – availability of at least two consecutive MRI scans (T1 with contrast) [6], availability of binary tumor segmentation masks, interval between scans of at least 6 months. After filtering, 96 patients were obtained for analysis.

Itoyama et al. [22] investigated risk factors for rapid vestibular schwannoma growth based on radiomics features of T1-weighted images, achieving AUC = 0.69. Yang et al. [23] developed a machine learning model for predicting pseudoprogression and long-term outcomes after vestibular schwannoma radiosurgery, achieving accuracy of 88.4%.

III. Problem Statement

The task consists of binary classification: based on radiomics features of the first MRI scan, predict whether the tumor will grow by the time of the next examination.

Tumor volume was calculated using the formula:

$$V = N_{\text{voxel}} \cdot V_{\text{voxel}},$$

where N_{voxel} is the number of voxels in the segmentation mask; V_{voxel} is the volume of a single voxel (mm³).

Relative volume change is determined as:

$$\Delta V = \frac{V_2 - V_1}{V_1} \cdot 100\%,$$

where V_1 is the volume at the first scan, V_2 is the volume at the second scan.

Class label is assigned according to the rule:

$$y = \begin{cases} 1, & \text{if } \Delta V > 10\% \\ 0, & \text{else} \end{cases}$$

The 10% threshold was chosen based on clinical practice and ensures a balanced class distribution: 40 patients (41.7%) with growth, 56 patients (58.3%) without growth.

IV. Proposed Approach

The proposed approach consists of several stages, namely: extraction of radiomics features, wavelet decomposition, feature selection, and formation of the Voting ensemble.

Radiomics features were extracted from the first MRI scan of each patient using the PyRadiomics library [24]. Extraction settings: – Bin width (binWidth): 25 – Intensity normalization: enabled – Mask correction: enabled.

To increase the informativeness of features, a wavelet filter was applied using the Coiflet-1 wavelet. Three-dimensional decomposition decomposes the image into 8 components according to the discrete wavelet transform formula:

$$W(j,k) = \sum_n x(n) \cdot \psi_{j,k}(n),$$

where $\psi_{j,k}(n)$ is the wavelet function at scale and shift; k, $x(n)$ is the input signal.

For each of the 8 wavelet components, 93 texture features were extracted (shape features were excluded due to potential data leakage), yielding a total of 744 features.

To reduce dimensionality and prevent overfitting, the SelectKBest method with ANOVA F-score criterion was applied [25]:

$$F = \frac{SS_{\text{between}}}{SS_{\text{within}}} = \frac{\sum_i n_i (\bar{x}_i - \bar{x})^2 / (k-1)}{\sum_i \sum_j (x_{ij} - \bar{x}_i)^2 / (N-k)},$$

where SS_{between} is the between-group variance; SS_{within} is the within-group variance; k is the number of classes; N is the total number of samples.

Based on experiments, k = 5 most informative features were selected, which corresponds to the rule $k \approx \sqrt{N}$ for small samples.

A Voting ensemble with soft voting was proposed, combining five base classifiers [20].

Support Vector Machine (SVM) with RBF kernel solves the optimization problem [26]:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i,$$

subject to $y_i\left(w^T\phi(x_i)+b\right)\geq 1-\xi_i$, where C is the regularization parameter.

Logistic regression models the class probability [27]:

$$P(y=1\,|\,x)=\frac{1}{1+e^{-\left(w^T x+b\right)}},$$

k-Nearest Neighbors (k-NN) classifies based on voting of k nearest neighbors [28]:

$$\hat{y}=\arg\max_{c}\sum_{i\in N_k(x)}\mathbb{I}\left(y_i=c\right),$$

where $N_k(x)$ is the set of k nearest neighbors of point x.

Random Forest – ensemble of decision trees with random feature selection [29]:

$$\hat{y}=\frac{1}{B}\sum_{b=1}^{B}f_b(x),$$

where B is the number of trees; f_b is the b-th tree. Linear Discriminant Analysis (LDA) finds a linear combination of features that maximizes the ratio of between-class to within-class variance [30]:

$$J(w)=\frac{w^T S_B w}{w^T S_W w},$$

where S_B is the between-class scatter matrix; S_W is the within-class scatter matrix.

The Voting ensemble averages class probabilities from base classifiers:

$$\hat{y}=\arg\max_{c}\sum_{j=1}^{M}w_j\cdot P_j(y=c\,|\,x),$$

where M is the number of classifiers, w_j is the weight of the j-th classifier (in our case $w_j=1/M$), $P_j(y=c\,|\,x)$ is the probability of class c by the j-th classifier.

The advantage of soft voting is accounting for the confidence of each classifier in its prediction, unlike hard voting, where only the winning class is considered.

V. RESULTS

For model evaluation, 5-fold stratified cross-validation (Stratified 5-Fold CV) was applied, which preserves class proportions in each fold [31].

The primary metric — ROC AUC (Area Under the Receiver Operating Characteristic Curve):

$$\mathrm{AUC}=\int_0^1 \mathrm{TPR}\left(\mathrm{FPR}^{-1}(t)\right)dt,$$

where TPR is the True Positive Rate (sensitivity), FPR is the False Positive Rate. Additionally, accuracy was computed as the proportion of correct predictions.

The study was implemented in Python 3.10 using PyRadiomics 3.0 [24] and scikit-learn 1.3 libraries.

Table I presents the results of individual classifiers on wavelet features with selection of k = 5 best features.

TABLE I. RESULTS OF INDIVIDUAL CLASSIFIERS (5-FOLD CV)

Classifier	Accuracy	ROC AUC	± std
Gradient Boosting	0.656	0.713	0.167
Random Forest	0.635	0.712	0.116
Logistic Regression	0.625	0.710	0.089
SVM	0.615	0.709	0.091
k-NN (k = 5)	0.604	0.698	0.095
LDA	0.594	0.695	0.102

The best result among individual classifiers was achieved by Gradient Boosting (AUC = 0.713), however with high variability (std = 0.167).

Various combinations of classifiers in the Voting ensemble were investigated. Results are presented in Table II.

The best result was achieved by the ensemble of 5 classifiers: SVM + Logistic Regression + Random Forest + k-NN + LDA with ROC AUC = 0.742 ± 0.072.

Key observations:

1) Adding LDA to the base ensemble (4 models) improved the result from 0.736 to 0.742.

2) Adding Gradient Boosting worsened the result despite its high individual performance.

3) Increasing the number of models beyond 5 does not improve the result.

TABLE II. RESULTS OF VOTING ENSEMBLES (5-FOLD CV)

Combination	Accuracy	ROC AUC	± std
SVM+LR+RF+kNN+LDA	0.656	0.742	0.072
SVM+LDA+RF+kNN	0.646	0.738	0.072
SVM+LR+ET+kNN	0.635	0.738	0.086
SVM+LR+RF+kNN	0.646	0.736	0.070
SVM+LR+RF+kNN+GB	0.625	0.718	0.076
SVM+LR+RF+kNN+ET+GB	0.615	0.718	0.074

Comparison of different ensemble combinations is visualized in Fig. 1.

Table III demonstrates the improvement of results at each stage of the study.

TABLE III. EVOLUTION OF RESULTS

Stage	Approach	ROC AUC	Improvement
Baseline	Original Radiomics + SVM	0.646	—
+ Wavelet	Wavelet features + GB	0.713	+10.4%
+ Ensemble	Wavelet + Voting (5 models)	0.742	+14.9%

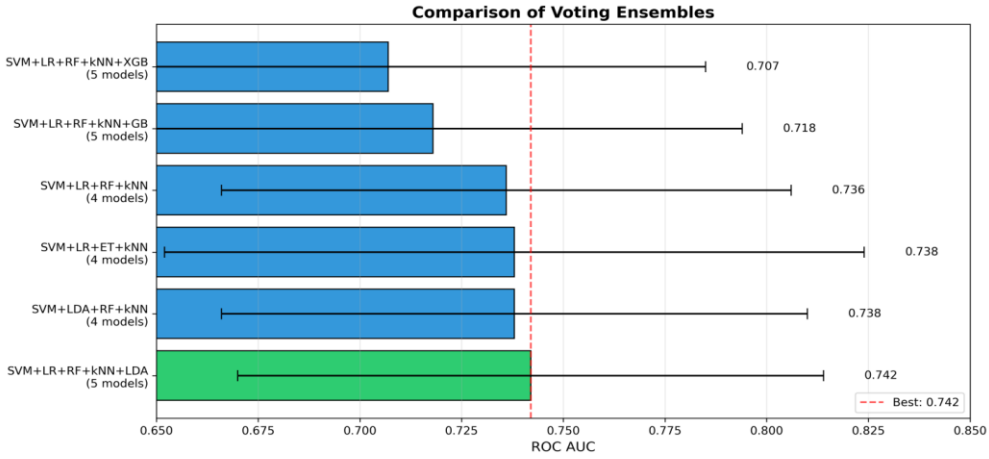

Fig. 1. Comparison of ROC AUC for different classifier combinations in the Voting ensemble. The best result (AUC = 0.742) was achieved by the SVM + LR + RF + kNN + LDA combination

Application of wavelet decomposition and the ensemble method improved ROC AUC from 0.646 to 0.742, representing an improvement of 14.9%.

Table IV presents the top-5 features selected by the SelectKBest method using the ANOVA F-score criterion.

Analysis of selected features demonstrates several important patterns:

1) Dominance of the Skewness metric – intensity distribution asymmetry is the most informative characteristic. Three of the five top features are Skewness metrics from different wavelet components.

2) Importance of high-frequency components – features from HHH, HLH, and LHL components containing high-frequency information proved to be the most significant. This suggests that fine texture details of the tumor correlate with its subsequent growth.

3) Statistical significance – all top-5 features have p-value < 0.05, confirming their prognostic value.

Visualization of the importance of top-10 features is presented in Fig. 2.

TABLE IV. MOST INFORMATIVE FEATURES FOR TUMOR GROWTH PREDICTION

No	Feature	Wavelet	Matrix	F-score	p-value
1	Skewness	HHH	First Order	10.63	0.0016**
2	Skewness	LHL	First Order	10.14	0.0020**
3	Skewness	HLH	First Order	6.59	0.0118*
4	Correlation	HLH	GLCM	6.52	0.0123*
5	Median	LLH	First Order	5.54	0.0207*

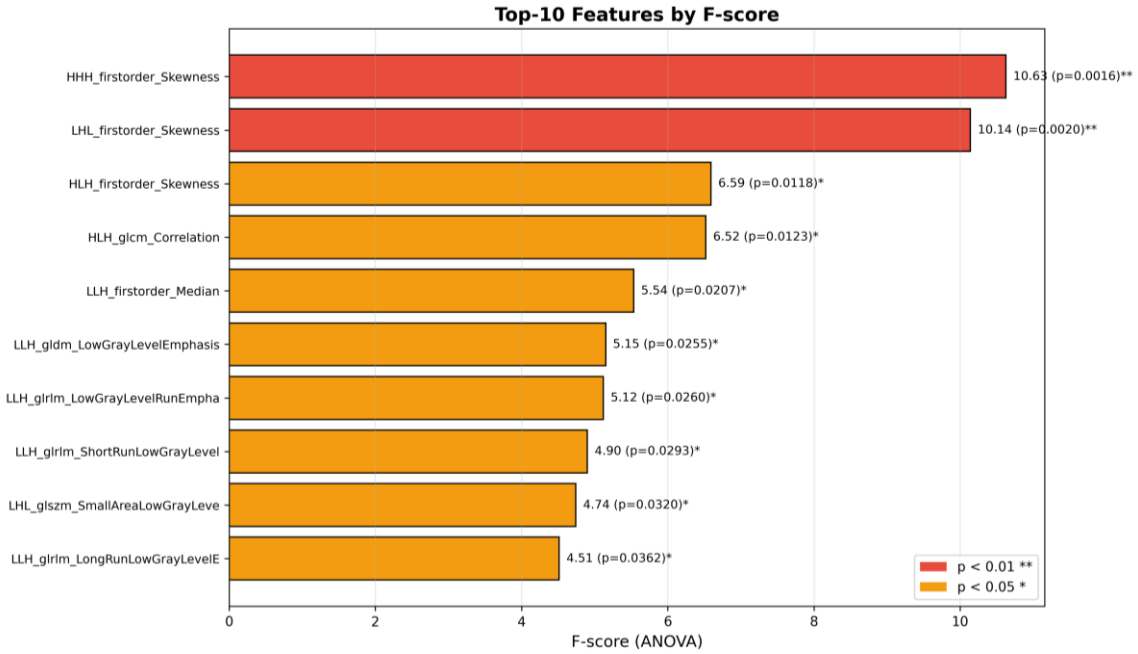

Fig. 2. Top-10 features by ANOVA F-score criterion. Color indicates the level of statistical significance: red – $p < 0.01$, yellow – $p < 0.05$

VI. Conclusion

This paper proposes a method for predicting vestibular schwannoma growth based on radiomics features of a single MRI scan. The main results of the study:

1) Wavelet decomposition significantly increases the informativeness of radiomics features, allowing the detection of texture patterns at different scales.

2) The Voting ensemble of five diverse classifiers (SVM, LR, RF, k-NN, LDA) provides the best and most stable prediction quality compared to individual models.

3) ROC AUC of 0.742 ± 0.072 was achieved, which exceeds the baseline result (0.646) by 14.9% and is competitive with the results of existing studies.

4) Feature selection is critically important for small samples: the optimal number of features k = 5 for 96 samples.

5) Complex ensemble methods (XGBoost, Gradient Boosting) demonstrate overfitting on small samples, while simple models perform more stably.

The practical significance of the proposed method lies in the ability to predict tumor behavior already during the patient's first visit, which allows optimizing the surveillance strategy and timely planning of treatment.

Limitations of the study include the relatively small sample size (96 patients) and the lack of external validation on an independent dataset.

Prospects for further research include validation on larger samples, integration of clinical data, and application of deep learning methods.

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В. М. Синєглазов, Шевченко М. В. Прогнозування росту вестибулярної шванноми на основі радіоміксних ознак МРТ зображень із застосуванням ансамблевих методів машинного навчання.
У роботі запропоновано метод прогнозування росту вестибулярної шванноми на основі аналізу одного МРТ-знімка з використанням радіоміксних ознак та ансамблевих методів машинного навчання. Досліджено 96 пацієнтів з публічного датасету Vestibular-Schwannoma-MC-RC2. Витягнуто 744 текстурні ознаки за допомогою wavelet-декомпозиції. Запропоновано ансамбль Voting, що поєднує п’ять класифікаторів: SVM, LR, k-NN, Random Forest та LDA. Досягнуто ROC AUC = 0.742 ± 0.072 при 5-кратній крос-валідації. Результати підтверджують ефективність запропонованого підходу для раннього прогнозування росту пухлини.
Ключові слова: вестибулярна шваннома; радіоміксні ознаки; машинне навчання; ансамблеві методи; вейвлет-декомпозиція; прогнозування росту пухлини.

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Кількість публікацій: більше 820 наукових робіт.
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