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Pleomorphic Adenoma of the Parotid Gland – Histopathological, Neurological, Intraoperative and Machine Learning Insights

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Abstract: Pleomorphic adenoma (PA) is the most common benign tumour of the salivary glands, accounting for up to two-thirds of all salivary gland tumors. It most frequently occurs in the parotid gland and typically presents as a slow-growing, asymptomatic mass, predominantly affecting females between the third and sixth decades of life. Histologically, PA exhibits a mixed composition of epithelial, myoepithelial, and mesenchymal components embedded in a myxoid or chondroid stroma, with eosinophilic cytoplasm in polygonal myoepithelial cells. Although often well-circumscribed and localized in the superficial lobe of the parotid, PA can extend into deeper regions, including the parapharyngeal space, which complicates surgical management due to the proximity of critical neurovascular structures. This study aims to highlight the histopathological features of pleomorphic adenoma and correlate them with intraoperative findings. Advanced imaging techniques, particularly MRI, are crucial for accurate preoperative assessment, as delayed surgical intervention increases the risk of malignant transformation into carcinoma ex-pleomorphic adenoma, a more aggressive entity associated with recurrence and metastasis. In recent years, machine learning and deep learning models applied to MRI and ultrasound imaging have demonstrated significant potential in differentiating pleomorphic adenoma from other benign and malignant parotid tumours, improving diagnostic accuracy and supporting earlier clinical decision-making. Microscopic findings confirmed characteristic features of PA, including epithelial proliferation, myoepithelial components, haemorrhagic zones, eosinophilic stroma, and incomplete tumour capsules. Additionally, recent AI-assisted radiomic and convolutional neural network approaches have been shown to complement classical histopathology by extracting high-dimensional imaging features that enhance tumour subtype classification and prognostic assessment. When integrated with clinical and imaging data, these machine learning techniques offer promising avenues for reducing diagnostic uncertainty, optimising surgical planning—particularly in relation to facial nerve preservation—and contributing to more personalised management strategies in parotid gland pathology.

Keywords: pleomorphic adenoma; parotid gland; histopathology; myoepithelial cells; intraoperative findings.

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1. Introduction

Pleomorphic adenoma (PA), by far the most frequent salivary gland tumour, is categorised as benign mixed tumours (BMTs) due to its dual origin in epithelial and myoepithelial cells. It represents the most frequent of all salivary gland tumours (SGTs), accounting for up to two-thirds of the total (Lee et al., 2019; McLoughlin et al., 2018; Meshram, Kaur & Hura, 2018).

Most studies estimate that it accounts for 45–75% of all salivary gland tumours. Pleomorphic adenoma affects people of all ages, however it is most frequent in the third to sixth decades of life. Females have a relatively greater incidence of pleomorphic adenomas than males. Pleomorphic adenomas make up 70–80% of benign SGTs and are particularly common in the parotid gland (Pons Vicente et al., 2008).

Adenomas are most commonly found in the superficial lobe, although they may affect the gland's inner tissues and the parapharyngeal region. Pleomorphic adenoma typically manifests as a slow-progressing swelling that is asymptomatic (Sergi et al., 2008). Although PA primarily affects the parotid glands, it may also affect the hard and soft palate glands of saliva, cheek, the upper lip, the floor of the mouth, and tongue (Zhan et al., 2016).

Histological identification is the only way to definitively diagnose pleomorphic adenoma. The tumour is composed of three components: mesenchymal, myoepithelial cell, and epithelial cells. The discovery of these three elements serves as the theoretical basis for PA recognition. PA's histological appearance exhibits a varied epithelium within a loose fibrous stroma of the myxoid, mucoid or chondroid type. Polygonal in design, myoepithelial cells have a pale, eosinophilic cytoplasm (Zarbo, 2002).

Pleomorphic adenomas typically manifest as a well-defined, rounded mass or masses with a maximum diameter of less than 6 cm. PA often manifests as a unilateral hard mass that grows slowly and is asymptomatic; if left untreated, it may become larger. Due to the higher number of salivary glands in the soft and hard palates, pleomorphic adenomas of the minor salivary glands are more common there. These adenomas usually manifest as a solid or rubbery submucosal mass that either surrounds or does not have ulceration (Silva et al., 2006).

The anatomic placement of the parapharyngeal space, which lies behind the infra-temporal fossa, lateral to the nasopharynx, and anterior to the cervical column, makes management of these tumours more difficult. This region appears as an inverted pyramid, with the bottom portion created by the base of the skull (a small portion of the petrosal bone) and the peak defining the joint that connects the posterior belly of the digastric muscle and the greater cornu of the hyoid bone. The styloid process and its associated musculature are also present, along with the internal carotid artery, cranial nerves IX and XII, and the sympathetic chain (Sergi et al., 2008; Batsakis & Sneige, 1989).

Computed tomography (CT) and magnetic resonance imaging (MRI) are required diagnostic imaging tests. Because MRI better defines soft tissue and gives accurate information about tumour boundaries and their relationship to the structures around them, it is the preferred method (Kakimoto, 2009; Lee et al., 2008).

The more time that passes before surgery, the higher the chance of malignant transformation. Carcinoma ex pleomorphic adenoma is typically a tumour that is aggressive. About one-third of individuals with parotid tumours develop metastases, and almost half of patients experience recurrences (Roijs, 2002).

2. Connection Between Facial Nerve Injury During Parotid Gland Tumour Surgery and the Psychological Impact on Patients

A detailed knowledge of the complex anatomy of the facial nerve is crucial for accurate diagnosis, treatment and prognosis of facial nerve palsy. The facial nerve (the seventh cranial nerve) is classically divided into three segments: the origin segment, the intratemporal segment and the extratemporal segment, each with distinct anatomical and functional characteristics. Its origin is in the lower part of the pons, where the motor nucleus emerges at the cerebellopontine angle, close to

the anteroinferior cerebellar artery. An important element is the intermediate nerve, formed by sensory and autonomic fibres originating from the tractus solitarius and the superior salivatory nucleus, which joins the motor root. Subsequently, the facial nerve crosses the internal acoustic meatus (IAM) in the petrous portion of the temporal bone, occupying the anterosuperior compartment, together with the vestibulocochlear nerve and the labyrinthine artery, without giving off branches in this region.

In the intratemporal portion, the facial nerve traverses three distinct segments. The labyrinthine segment, the narrowest and most exposed, extends from the internal acoustic meatus (IAM) to the geniculate ganglion, where the nerve makes its first marked bend (first genu). At this point, the greater petrosal nerve branches off, carrying parasympathetic fibres to the pterygopalatine ganglion, which plays a role in controlling lacrimal secretion and the nasal and palatine glands. Lesions in this area can cause lacrimation disorders, hyperacusis (due to damage to the stapedius nerve), and loss of taste in the anterior two-thirds of the tongue (due to damage to the chorda tympani).

The tympanic segment follows the medial wall of the tympanic cavity, passing between the malleus and incus before the second genu, where the nerve makes a second bend. Nearby anatomical landmarks include the oval window, the lateral semicircular canal, and the cochlear process. The mastoid segment runs from the second genu to the stylomastoid foramen and gives off important branches, including the stapedius nerve and the chorda tympani, responsible for innervation of the submandibular and sublingual glands through the submandibular ganglion.

After crossing the stylomastoid foramen, the extratemporal segment of the facial nerve continues its course through the parotid gland, where it divides into the temporofacial and cervicofacial branches, then splits into five main branches: temporal, zygomatic, buccal, mandibular, and cervical. These branches innervate the muscles involved in facial expressions, and clinical assessment often focuses on their function (for example, the frontalis muscle for raising the eyebrows or the orbicularis oculi for closing the eyes).

Before reaching the parotid gland, the nerve also sends branches to the occipital, stylohyoid, and posterior portion of the digastric muscles. A good knowledge of this detailed anatomy is essential for the correct localisation of lesions, the estimation of clinical deficits, and the planning of surgical or medical treatments. (Karunarathna et al., 2025)

The facial nerve plays a crucial role in many functions of the face, including facial expression, taste perception, salivary and lacrimal secretion, middle ear sensation, and protection of the surface of the eyes. Facial paralysis is defined by the total inability to move the facial muscles, while facial paresis indicates only a weakening of the muscles, without complete loss of nerve function. The causes of FP are varied and may include Bell's palsy, infections, tumours, trauma, congenital factors, or iatrogenic or non-medical injuries. Facial paresis can reduce the perception of quality of life and precipitate emotional problems such as anxiety and depression (Gandolfi, 2016).

Facial paralysis can cause a wide range of emotional experiences in patients. Many feel that their face no longer looks “normal” or have difficulty expressing feelings and communicating with others, which can cause them to feel isolated and misunderstood. Studies show that people affected by this condition are at higher risk of anxiety and depression compared to the general population.

A study by Rist et al., using the Generalised Anxiety Disorder-2 (GAD-2), Patient Health Questionnaire-2 (PHQ-2), and quality of life (QOL) scores, found that 23% of patients had depressive symptoms, and those with positive results for anxiety and depression reported lower quality of life scores.

Depression represents the most common emotional reaction seen in patients with facial palsy, occurring in approximately 31% of patients. Typical symptoms include persistent worry, loss of interest in activities, feelings of worthlessness, difficulty making decisions, feelings of hopelessness, dissatisfaction, and problems concentrating. The inability to smile and express emotions is often perceived as the most difficult aspect of the disease. Saadi et al. reported a

significant increase in depression after the onset of FP, regardless of previous depression. Pouwels and his team also observed a much higher rate of depression in patients with facial paralysis compared to healthy individuals. Within this group, 25% had a depressive disorder, with mild to moderate forms predominating. Other studies confirm this trend, emphasising that patients with FP require psychological support integrated into the treatment plan.

Facial paralysis can cause social anxiety and fear of rejection among sufferers. Many fear negative reactions from others, feel isolated, or are stigmatised because of the condition, leading to chronic anxiety and withdrawal from daily activities. These fears are often exacerbated by previous unpleasant experiences, such as being stared at by strangers and by reduced self-confidence. For many individuals, sexuality is already a sensitive topic, and for those affected by this condition, insecurity and difficulty connecting with their own sexual dimension can exacerbate the problem. People affected by disorders that alter the normal functioning of the face, such as facial palsy (FP), may perceive a profound change in their sense of self and relationships. In a qualitative study of patients with congenital FP, participants described difficulties in maintaining a connection with their own self; some reported difficulty recognising themselves in the mirror. Another study, conducted with patients with acquired FP, highlighted feelings of loss and distress over their former face and the challenge of constructing a new identity. One participant stated, “my face is no longer my face,” and others spoke of themselves in the third person, as if they were talking about someone else. These testimonies illustrate the frequent loss of a sense of identity and the process of mourning for a face that was lost or never had.

The most commonly used instruments to assess the quality of life of patients with facial paralysis are the Facial Disability Index (FDI) and the Facial Clinimetric Evaluation (FaCE) scale. The FDI analyses non-motor aspects of the disease, such as how patients carry out their daily activities, the degree of disability, psychosocial factors and the results of therapeutic interventions. This questionnaire includes two subscores: one for physical function and another for social function and well-being. The FaCE scale, also a self-assessment questionnaire, measures the frequency and severity of physical and psychosocial problems of facial function, such as facial movements, facial and ocular comfort, oral function, tear control and social interactions. Both instruments, the FDI and the FaCE, were designed to highlight the psychosocial difficulties specific to facial paralysis, which cannot be captured by strictly objective measurements. (Vargo et al., 2023)

The primary aim of the following study was to assess the relationship between depression, quality of life (QOL) and facial paralysis. As a secondary objective, the research aimed to identify the probability of obtaining a positive result on screening for mild depression in both the facial paralysis group and the control group. It was also desired to compare the mean values of the scores for quality of life, depression, attractiveness and general mood between patients with facial paralysis and participants in the control groups.

Between October 2013 and March 2016, a total of 263 patients were prospectively recruited. Of these, 250 participants completed the questionnaires in full, representing a response rate of 95.1%, while 13 patients were excluded from the analysis. The majority of participants were white (79%), female (67%), married or engaged (63%), and held a university degree (36%). The mean age was 49 years. In total, 88 patients were in the facial palsy group, and 175 were in the control group. Comparison of gender distribution between groups did not reveal significant differences ($\chi^2_1 = 0.061$; $P = 0.81$). In the facial palsy group, the most common aetiologies were acoustic neuroma resection (31.8% of patients) and Bell's palsy (29.6%).

Additional hypothesis analyses, adjusted for multiple comparisons, revealed that individuals with facial paralysis scored significantly higher on the depression scale ($t_{(248)} = -7.17$, $P < 0.001$) and, at the same time, had significantly lower scores on both quality of life (QoL; $t_{(261)} = 7.07$, $P < 0.001$), self-rated attractiveness ($t_{(256)} = 5.93$, $P < 0.001$), and general mood ($t_{(261)} = 5.79$, $P < 0.001$). In conclusion, 37 patients with facial paralysis and 13 controls screened positive for depression, even mild depression. The proportion of those who screened positive was significantly higher in patients with facial paralysis (42.1%) than in controls (8.1%; $\chi^2_{(1)} = 40.92$, $P < 0.001$). The

depression rate in the controls, which were predominantly female, was consistent with the prevalence reported in the general United States population (7.6%). There was also no significant association between the cause of facial paralysis and positive depression screening results ($\chi^2_{(10)} = 0.061$, $P = 0.93$). Previous research has shown a link between facial deformities and female gender, on the one hand, and the occurrence of depression, on the other. Facial paralysis has also been associated with a lower quality of life (QOL). However, significant differences in quality of life between men and women have not been identified. Sensitivity analysis for missing data, performed by multiple imputation, did not show significant variations, so the simplified model was retained. According to this model, facial paralysis and female gender were significantly correlated with higher depression scores [95% CI, 0.77–3.39]; effect of facial paralysis: [95% CI, 4.38–7.58]; effect of female gender: [95% CI, 0.65–3.25]. At the same time, facial paralysis is associated with decreased QOL scores [95% CI, 78.98–84.25]. Ishii and colleagues have shown that people with facial paralysis have difficulty expressing emotions and are perceived as having a low level of attractiveness. The asymmetry characteristic of this condition also causes a noticeable distraction. These results highlight the negative consequences that facial paralysis can have on social relationships. In a study conducted by Bradbury and colleagues, based on structured interviews, 89.6% of patients with facial paralysis reported receiving intrusive questions about their appearance from strangers and acquaintances, and half of them felt a significant psychological impact. Such experiences affect self-perception, discourage social contact, and promote isolation. Over time, internalising these negative interactions can alter patients' self-image. Our results support this conclusion, showing that patients with facial paralysis rate their attractiveness significantly lower than those without the condition. In addition, the psychosocial stress associated with facial paralysis may contribute to the onset of depression. (Nellis et al., 2017)

3. Neurological Outcomes and Prognostic Significance of Facial Nerve Damage in Parotid Gland Neoplasms

Damage to the facial nerve in the context of parotid gland neoplasms is a critical clinical issue with consequences that extend beyond immediate functional loss. Its presence influences prognosis, dictates surgical strategy, and may lead to specific postoperative complications. Understanding these neurological outcomes is essential for optimising patient management and improving long-term survival and quality of life.

3.1. Prognostic Impact of Facial Nerve Palsy

Facial nerve palsy represents more than a functional impairment; it also holds significant prognostic value. Patients presenting with facial paralysis and evidence of perineural spread have a markedly increased risk of recurrence and mortality compared to those without such findings. Clinical evidence indicates that these neurological features serve as strong predictors of poor long-term survival in parotid carcinoma (Terhaard et al., 2006; Terakedis, 2017)

3.2. Surgical Management and Functional Recovery

In surgical practice, preservation of the facial nerve remains the primary objective. However, when tumour infiltration is evident, partial or complete resection of the nerve may be required to achieve oncologic clearance. In such cases, nerve grafting or reanimation procedures are employed to restore motor function. Reported outcomes suggest that patients undergoing nerve reconstruction often achieve intermediate recovery (House-Brackmann grade III–IV) within 12 months (Preis et al., 2010; Park et al., 2019).

3.3. Neurogenic Neoplasms of the Parotid

Although rare, primary neurogenic tumours—including schwannomas and neurofibromas—can arise within the parotid gland. Intraparotid facial nerve schwannomas, which account for only a minority of facial nerve schwannomas, typically demonstrate slow growth and

displacement rather than infiltrate neural fascicles, often explaining the absence of preoperative palsy. Conversely, neurofibromas may involve distal branches of the nerve, occasionally requiring their resection and resulting in transient or permanent weakness. Partial recovery may be achieved through physiotherapy (Facial Nerve Schwannoma, 2015; Intraparotid Neurofibroma, 2022).

3.4. Postoperative Neurological Sequelae: Frey's Syndrome

A well-recognised postoperative complication of parotidectomy is Frey's syndrome, characterised by gustatory sweating and erythema of the cheek during mastication. This condition results from aberrant parasympathetic regeneration targeting sweat glands in the overlying skin. Reported incidence ranges from 30% to 50%, though it is likely underestimated as mild cases may go unnoticed.

3.5. Neurological Risk by Tumour Origin

Comparative studies emphasise that parotid tumours of neurogenic histology carry a substantially greater risk of persistent neurological impairment than tumours of salivary origin. Meta-analyses reveal that nearly half of patients with neurogenic tumours experience postoperative neurological deficits, whereas the incidence is considerably lower in salivary gland tumours. These findings underscore the importance of precise preoperative diagnosis and meticulous surgical planning (Neurological Complications in Parapharyngeal Tumors, 2023).

4. Deep Learning Architectures and Imaging Modalities for the Diagnosis and Prognosis of Parotid Gland Tumours

This section discusses how advanced deep learning architectures can be integrated with different imaging techniques to improve the diagnosis, classification, and prognostic assessment of parotid gland tumours. Various methods are presented, including both MRI and ultrasound-based approaches.

In the first part, studies using modified versions of the ResNet18 model with multichannel MRI data are highlighted, demonstrating that tumour segmentation and image augmentation can increase the accuracy of classification between benign and malignant lesions. The role of graphical user interfaces (GUIs) is also analysed, which facilitates clinical application.

Subsequently, radiomic methods with T2-weighted MRI sequences are described, in which machine learning algorithms such as logistic regression, support vector machines, and k-nearest neighbours are used to extract and analyse highly complex imaging features.

The chapter continues by discussing the use of dynamic contrast-enhanced MRI (DCE-MRI) in conjunction with convolutional neural networks, as well as advanced deep learning models such as MobileNetV2 and EfficientNetB0, to optimise tumour subtype differentiation.

Ultrasound-based diagnostic models are also presented, including architectures such as SqueezeNet and ResNet, with special attention paid to their performance compared to that of radiologists. Automated segmentation methods such as Deeplabv3 and UNet are mentioned as useful tools for identifying regions of interest and training the networks. In addition, the chapter reviews the application of artificial neural networks (ANNs) to predict the occurrence of facial nerve palsy after parotid gland surgery.

Finally, innovative solutions are highlighted, such as 3DPalsyNet, which shows the potential of 3D convolutional neural networks in assessing the degree of facial paralysis and movement recognition, extending the applicability of deep learning beyond tumour classification to functional assessment. Overall, these methods highlight the ability of artificial intelligence to support clinical decisions, reduce diagnostic uncertainty, and personalise therapeutic strategies in parotid gland pathology.

4.1. Modified ResNet18 with Multichannel MRI Input

Data were collected in a study including 233 patients treated between 2014 and 2018 at Fudan University Shanghai Cancer Centre, with a mean age of 52 years. Histopathological results were obtained through surgical intervention, and information was retrieved from the Electronic

Medical Record System (EMR). Tumours were categorised as benign (pleomorphic adenoma and Warthin tumour) and malignant (adenocarcinoma). Patients were examined by MRI, including at least three series (T1, T2 and T1 with contrast agent), as illustrated in Figure 1. The segmentation of the parotid gland and the region of interest was performed by a radiologist through segmentation based on MRI images, in order to improve the performance of the deep learning model. Following MRI segmentation and examination, 3791 images of the parotid region were cropped.

For model training, all data were randomly divided into training and testing groups. The training set included 714 pleomorphic adenoma slices, 558 Warthin tumour slices, 861 adenocarcinoma slices, and 902 slices without lesions. The testing set consisted of 186 slices, of which 93 were adenocarcinoma, 57 were pleomorphic adenoma, 36 were Warthin tumour, and 89 of them were without lesions.

The network is based on ResNet18 with input images of 224×224 pixels, as illustrated in Figure 2. Techniques such as colour jitter, affine transformation, random image flipping, and contrast adjustment were used to augment the data. Optimised Adam and the cross-entropy function were also used. The model was trained on an Intel i7-8700K CPU and an Nvidia GeForce 1080 Ti GPU. PyTorch was used to develop the programme.

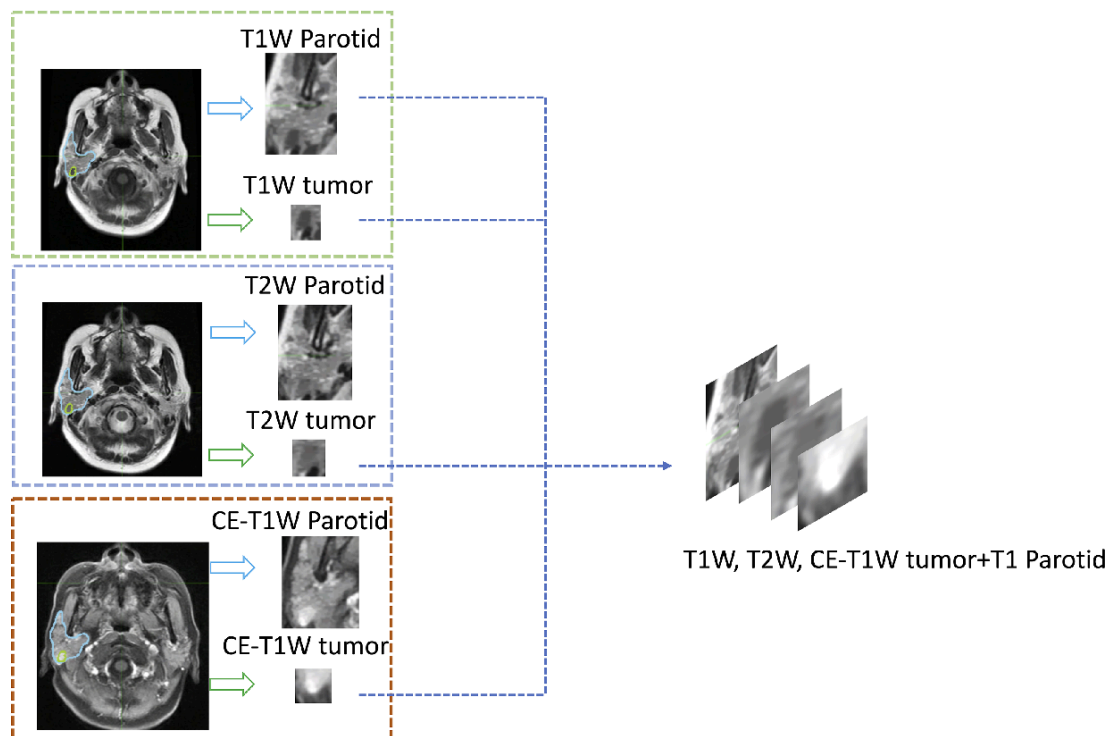


Figure 1. An illustration of the four-channel input

Source: Xia, X., Feng, B., Wang, J., Hua, Q., Yang, Y., Sheng, L., Mou, Y., & Hu, W. (2021). Deep learning for differentiating benign from malignant parotid lesions on MR images. *Frontiers in Oncology*, 11, 632104. <https://doi.org/10.3389/fonc.2021.632104>

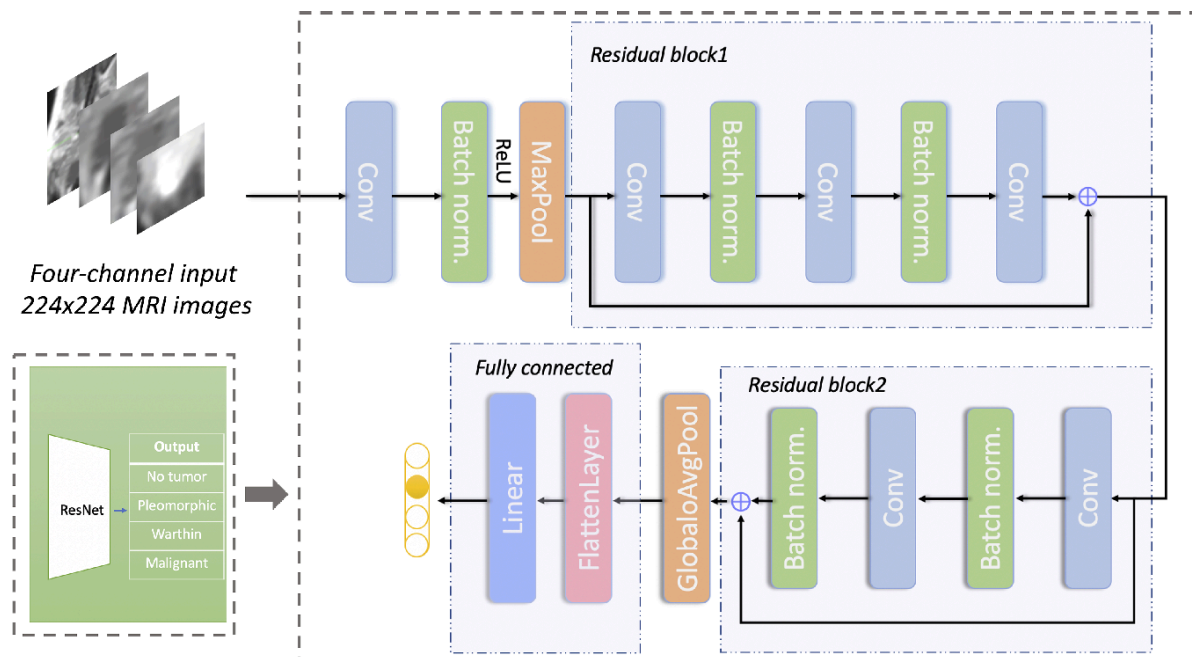


Figure 2. Prediction of parotid gland tumor types using ResNet

Source: Xia, X., Feng, B., Wang, J., Hua, Q., Yang, Y., Sheng, L., Mou, Y., & Hu, W. (2021). Deep learning for differentiating benign from malignant parotid lesions on MR images. *Frontiers in Oncology*, 11, 632104. <https://doi.org/10.3389/fonc.2021.632104>

The results showed that for the training set, the accuracy of image classification was 92% and for the testing set it was 82%. The optimal performance was achieved when images of the parotid gland contour were combined with the three MRI sequences (T1-weighted, contrast-enhanced T1-weighted [CE-T1], and T2-weighted). This model achieved an accuracy of 0.882 in differentiating benign from malignant tumours, with an accuracy of 63% in distinguishing pleomorphic adenoma from Warthin tumours. For the final diagnosis and staging of parotid cancer, the results showed an algorithm accuracy of 82% (95% CI, [0.77,0.86]) with a micro-AUC of 0.93. For full validation, future multicentre studies are needed, however, the proposed model may support clinicians in diagnosis of parotid tumours. (Xia et al., 2021)

4.2. Deep Learning with ResNet18 and GUI Support in MRI-Based Diagnosis

The following study included a total of 113 patients with parotid gland tumours (histologically, 43 of these were pleomorphic adenomas, 45 Warthin tumours, 10 other benign tumours such as haemangiomas or lymph nodes, 9 mucoepidermoid carcinomas and 10 other malignant tumours such as adenocarcinoma or metastasis. As imaging methods, MRI was used with conventional protocols such as T1-w and T2-w, with a main role in determining the tumour size and the relationship with anatomical structures in proximity.

To improve the diagnostic accuracy of the malignant histology, parameters such as diffusion-weighted imaging (DWI) and apparent diffusion coefficient (ADC) were used, although Warthin tumours, with their unique histological features, did not follow this general rule. Using these selected sequences (ADC, DWI-0, DWI-200, T1-w, T2-w, T1c-w) this work sought to distinguish benign from cancerous tumours, pleomorphic adenomas from Warthin tumours, respectively to differentiate Warthin tumours from malignant ones.

This investigation used ResNet18, an 18-layer convolutional neural network, with an image input size of 224x 224x 3 pixels, a model that has the capacity to classify up to 1000 object categories. In addition, a graphical user interface (GUI) was designed to allow images to be loaded into the application in order to delineate between various subtypes. This developed model is the

innovative element, offering a new perspective within the specialised literature, as illustrated in Figure 3.

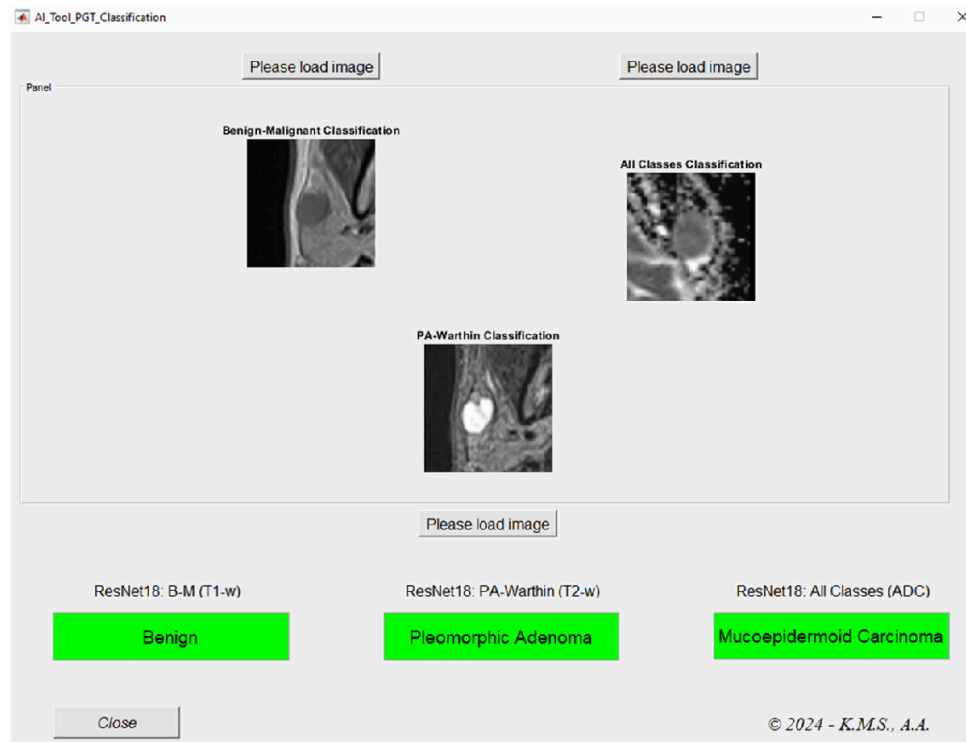


Figure 3. Screenshot of the GUI application designed for this study. Adapted from Kaba, E., Sunnetci, K. M., Alkan, A., & Beyazal Celiker, F. (2025). Magnetic resonance imaging-based differential diagnosis of parotid gland tumors using deep learning. *European Journal of Therapeutics*, 31(1), 44–50. <https://doi.org/10.58600/eurjther2612>

The results indicated that the architecture that discriminated between benign from malignant phenotype using the T2-w sequence had performance metrics of 93% with an F1 score of 94%. For the T1-w sequence, the highest outcome was achieved in the malignant versus Warthin classification with an accuracy of 95%. As for the T1c-w, ADC and DWI-2000 protocols, the differentiation between benign and malignant had an accuracy of 91%, 90% and 91% respectively. For the DWI-0 MRI protocol, a predictive capacity of 93% and an F1 score of 92% were observed concerning the malignant-Warthin images.

The conclusions of this research are that the highest diagnostic yield was in diagnostic distinction of non-cancerous vs malignant lesions with an accuracy of 93%, with the pre-contrast T1-w sequence outperforming the contrast-enhanced one in differentiating PA-Warthin and Warthin-malignant tumours. The analysis concluded that deep learning (DL) methods could reduce the need for contrast agents in imaging studies in the future, with potential implications for reducing costs and alleviating the burden of contrast administration. (Kaba et al., 2025)

4.3. T2-Weighted MRI Radiomics: Machine Learning for Differentiating Benign and Malignant Parotid Tumours

Considering that T2-weighted images (T2WI) provide a higher accuracy in distinguishing the internal structure of tumour formations compared with T1WI and can be obtained by MRI scanning without contrast agent, it was decided to select them for this research. For the diagnosis of pleomorphic adenomas, the radiomic model based on T2WI showed the highest accuracy. Using various machine learning methods for triple classification of parotid gland tumours, the study aimed

to develop and validate radiomic models based on MRI. A total of 147 patients with an average age of 53 years were included in this research, comprising 56 pleomorphic adenomas, 71 other benign tumours (of which 63 Warthin tumours) and 20 malignant tumours.

Using ITK-SNAP version 3.8, a radiologist delineated regions of interest based on T2WI images. The Pyradiomics software served to extract features, while image resampling and z-score normalisation were applied to achieve data reproducibility and proper preprocessing, as illustrated in Figure 4.

This approach was performed to assess intra- and inter-observer agreement, using intraclass correlation coefficients (ICC). Good consistency in the reproduction of extracted features was correlated with ICC values above 0.75. The Max-Relevance Min-Redundancy (mRMR) algorithm was used to minimise the number of feature dimensions. The Extreme Gradient Boosting algorithm was used to improve the accuracy of the predictions. Based on these data, radiomic models were developed using Support Vector Machine (SVM), k-Nearest Neighbor (KNN) and Logistic Regression(LR).

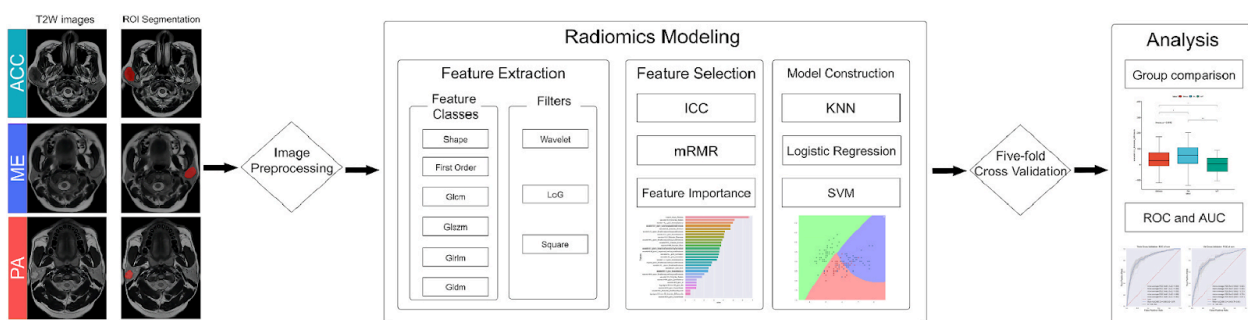


Figure 4. Development and validation of the radiomics model

Source: Guo, J., Feng, J., Huang, Y., Li, X., Hu, Z., Zhou, Q., & Xu, H. (2024). Diagnostic performance of MRI-based radiomics models using machine learning approaches for the triple classification of parotid tumors. *Heliyon*, 10, e36601. <https://doi.org/10.1016/j.heliyon.2024.e36601>

The three models were analysed and compared based on the receiver operating characteristic (ROC). Out of a total of 1,057 radiomic features extracted, eight were selected for building the radiomic model. The LR, SVM and KNN based models obtained AUC values of 0.85, 0.85 and 0.83 for the training set and 0.80, 0.80 and 0.79 for the validation set, indicating their ability to distinguish pleomorphic adenomas (PA) from malignant tumours (MT) and other benign formations of the parotid gland. These results indicate that T2WI-based radiomics provides good diagnostic performance and may assist clinical decision-making. (Guo et al., 2024)

4.4. Deep Learning and DCE-MRI: An Innovative Approach to Differentiating Benign and Malignant Parotid Tumours

Data were obtained from a retrospective study that included a total of 164 participants, of whom 124 had histopathologically confirmed parotid gland tumours and 40 had normal parotid glands. They underwent multiparametric MRI examinations, including dynamic contrast-enhanced (DCE) sequences. The aim was to differentiate and classify normal versus tumoural lesions (Task 1), benign vs. malignant appearance (Task 2), and to differentiate between various benign subtypes (Task 3). Two deep learning architectures were used, namely MobileNetV2 and EfficientNetB0. These models were designed to generate predictions from MRI sequences (T2, T1 with contrast, including DWI with a b-value of 800 s/mm²), including binary cross-entropy loss and the Adam optimiser as illustrated in Figure 5.

The obtained DCE metrics were included in the workflow of the deep learning network through an SVM (Support Vector Machine) algorithm to improve the classification process.

The SVM model used a radial basis function kernel, with the hyperparameter C set to 5 and a maximum limit of 10,000 iterations. The model was trained and tested in Python, using the scikit-learn library. For each classification task (MobileNetV2, EfficientNetB0 and the combined voting method), performance indicators – accuracy, precision, sensitivity (recall), and F1-score – were determined using Python 3.11 together with the scikit-learn 1.6 library. To obtain a robust statistical evaluation of the models' performance, 95% confidence intervals were calculated using the bootstrap procedure, thus ensuring reliable results on the test set.

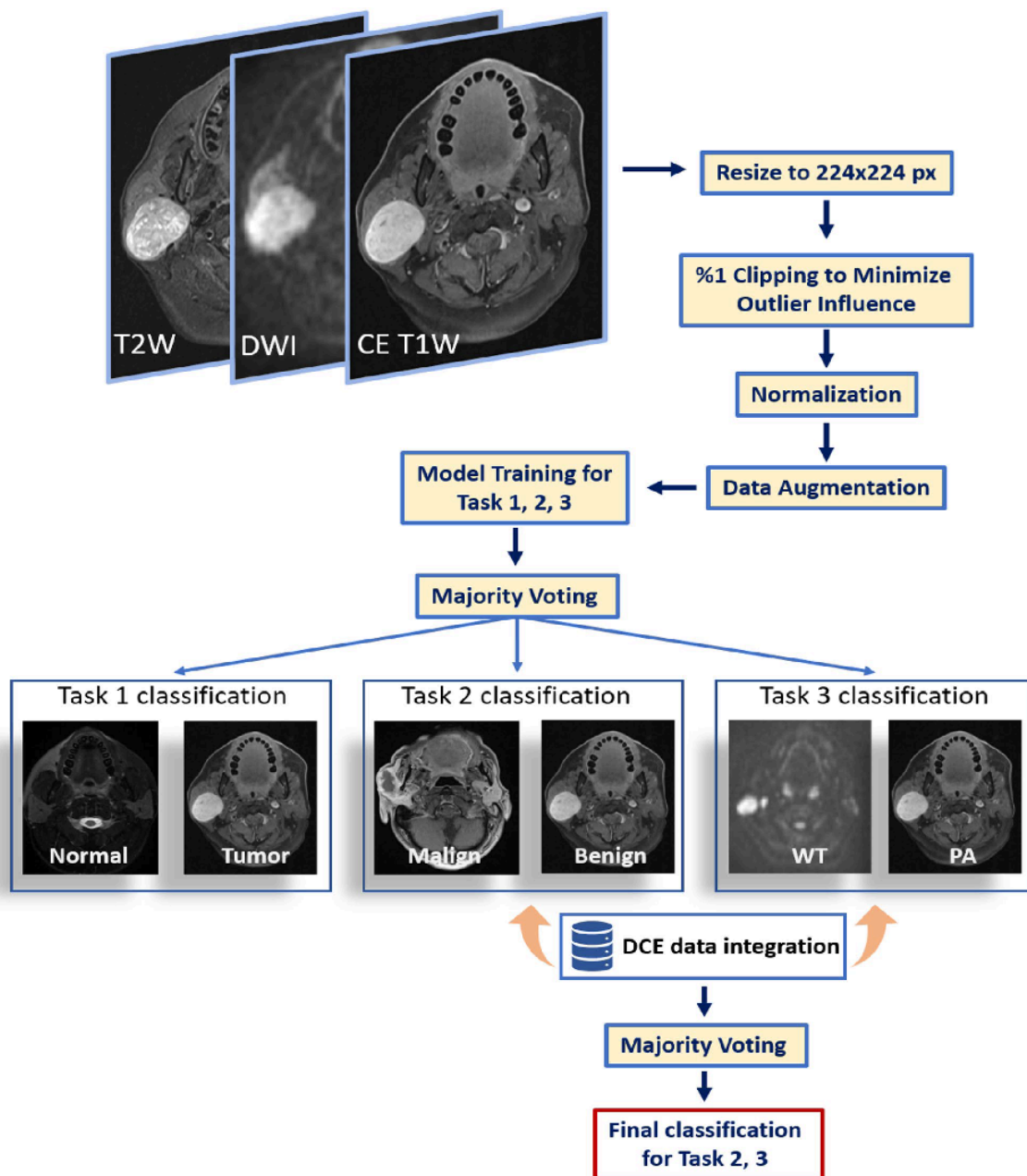


Figure 5. The preprocessing pipeline along with the model training workflow

Source: Sinci, K. A., Koska, I. O., Cetinoglu, Y. K., Erdogan, N., Koc, A. M., Ozkavruk Eliyatkin, N., Koska, C., & Candan, B. (2025). Deep learning-based classification of parotid gland tumors: Integrating dynamic contrast-enhanced MRI for enhanced diagnostic accuracy. *BMC Medical Imaging*, 25, 264.

<https://doi.org/10.1186/s12880-025-01814-x>

For differentiating normal from tumoural tissue, the accuracy was 77% with MobileNetV2 and 85% with EfficientNetB0. For the classification of benign versus malignant tumours, the performance was 56% for MobileNetV2 and 64% for EfficientNetB0. Regarding the differential diagnosis of benign tumours, the accuracy reached 53% with MobileNetV2 and 75% with EfficientNetB0. When using conventional MRI sequences (T2W, T1W with contrast and DWI), the EfficientNetB0 model demonstrated superior accuracy to MobileNetV2. However, both networks only provided moderate results, especially in identifying malignant tumours. Once the features extracted from DCE were integrated, the classification performance improved considerably, reaching up to 96% in separating benign from malignant lesions. (Sinci et al., 2025)

4.5. Deep Learning for Ultrasound-Based Detection of Parotid Tumour Features

This study included 266 patients, of whom 178 were diagnosed with benign parotid gland tumours and 88 with malignant tumours. The inclusion criteria comprised a clear histopathological diagnosis of a parotid gland tumour, preoperative ultrasound examination, and high-quality imaging without artefacts. The ultrasound images were included in the deep learning model in order to analyse and process them. For compatibility with the network model, an image resolution of 224 x 224 pixels was used. Considering that models such as ResNet and VGG16 are not the most suitable for diagnosis, as more complex calculations are required and they have a longer prediction time, SqueezeNet was chosen as the final model to extract features from ultrasonographic images and identify tumour type.

Although MobileNetV2 offered a shorter prediction time than SqueezeNet, its diagnostic accuracy was comparatively lower.

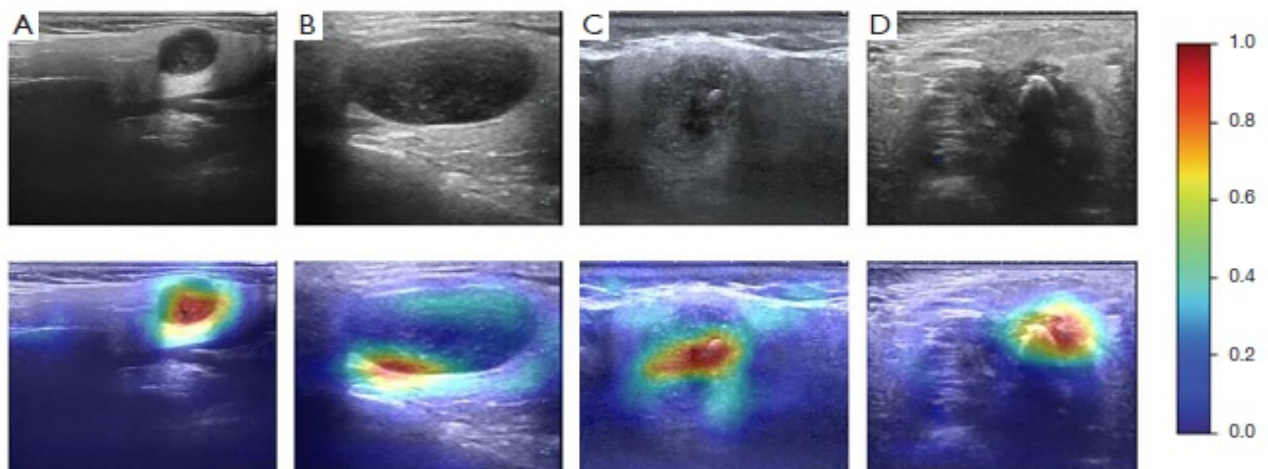


Figure 6. Based only on the tumor edge and the internal echogenicity, the learning model can predict the status of the parotid gland tumor even in grayscale ultrasound images. The regions highlighted in red and yellow have the highest predictive value, and those in green and blue have lower predictive value.

Source: Zhang, G., Zhu, L., Huang, R., Xu, Y., Lu, X., Chen, Y., Li, C., Lei, Y., Luo, X., Li, Z., Yi, S., He, J., & Zheng, C. (2023). A deep learning model for the differential diagnosis of benign and malignant salivary gland tumors based on ultrasound imaging and clinical data. *Quantitative Imaging in Medicine and Surgery*, 13(5), 2989–3000. <https://doi.org/10.21037/qims-22-950>

SqueezeNet is a fully convolutional network (FCN) that does not include a fully connected layer, but uses a large number of parameters. Its structure includes a convolution layer, a pooling layer, the ‘Fire’ module, and the Softmax layer, as illustrated in Figure 6. The ROC (Receiver Operating Characteristic) curve was used to evaluate the discrimination performance of the deep learning model in diagnosing parotid gland tumours. This reflects the sensitivity and specificity values. By calculating the F1- score, the performance of the model was assessed. All statistical

analyses were performed using IBM SPSS Statistics version 20.0. Ultimately, the database contained 458 ultrasound images obtained from 173 patients.

It was observed that the diagnostic outcomes of the radiologists were inferior compared to the deep learning (DL) model, regardless of the clinical data information. In the test set, a high diagnostic performance of the model was noted, with a specificity of 94%, sensitivity of 97%, accuracy of 95% and F1-score of 95%.

The results showed that after integration with clinical data, an outstanding diagnostic performance was obtained in terms of the diagnosis of parotid gland tumours, with an AUC of 0.9583, outperforming the best physician result of 0.8250. The sensitivity and specificity of this model surpassed those obtained with conventional ultrasound performed by the physician who also correlated the clinical data. Nevertheless, the study's single-center design and limited sample size warrant cautious interpretation and validation in larger multicenter cohorts. (Zhang et al., 2023)

Another study demonstrated how regions of interest (ROIs) were identified using an automatic segmentation algorithm. Established image segmentation algorithms such as Deeplabv3, UNet, and UNet++ were analysed, and based on the automatic segmentation of ultrasound images, an artificial intelligence-assisted diagnostic model for PGT was developed. A total of 582 patients were recruited from four centres, all with histopathologically confirmed benign or malignant tumours. Statistical analysis was performed using the independent samples t-test for the comparison of continuous variables between two groups, and the χ^2 test for the evaluation of discrete variables. All clinical characteristics were analysed univariately, with the odds ratio (OR) and the corresponding p-value being calculated for each variable.

Subsequently, clinical characteristics with p-value < 0.05 were used to develop clinical models. The variables highlighted in the univariate analyses were integrated into the models using three machine learning algorithms: logistic regression (LR), Random Forest, and XGBoost. Subvolumes were randomly extracted from the images, labelled according to positive or negative values, with a predefined spatial dimension and number of samples. During training, online data augmentation was applied, using techniques such as spacing and random cropping, thus generating numerous image variants during the training iterations.

The hyperparameters were selected as follows: the Adam optimiser was used with an initial learning rate of 1e-3, and the model was trained for 32 epochs with early stopping. All 2D rectangular ROIs were extracted from the raw ultrasound images according to the automatic 2D tumour segmentation mask. Six commonly used pretrained CNN models—DenseNet201, Inception_V3, ResNet101, ResNet18, ResNet50, and VGG19—were used.

For each patient, the section with the largest ROI was selected. The grey values were then normalised to the range [-1, 1] using min-max transformation. Due to the small amount of imaging data, the learning rate was carefully chosen to ensure good generalisation, and the learning rate cosine reduction algorithm was applied. To increase transparency and better understand the decision-making process of deep learning models, their visualisation and validation played a crucial role. Thus, to highlight the interpretability of deep learning-based radiomics, the Grad-CAM (gradient-weighted class activation mapping) method was used. The gradients extracted from the last convolutional layer of the CNN were used for weighted fusion, generating a class activation map that highlights key regions of the image for classification.

The entire process was carried out on an NVIDIA 4090 GPU board, using MONAI 0.8.1 and PyTorch 1.8.1. While the Deeplabv3 model provided the best performance in automatic segmentation, the results obtained with the deep learning models showed that ResNet18 had the best classification performance. This model had the lowest training loss, indicating fewer errors, and achieved a faster convergence rate than the other CNNs. In the internal validation set, ResNet18 achieved an AUC of 0.808, an accuracy of 0.765, a sensitivity of 0.750, and a specificity of 0.772. Using the optimal model resulted in a significant increase in clinical and overall benefits for two out of three radiologists. (Wei et al., 2024)

4.6. Artificial Neural Networks as a Tool for Predicting Facial Nerve Palsy in Benign Parotid Gland Surgery

During the study period, 356 patients underwent surgery for benign parotid gland tumours, but only 345 were included in the final analysis because of incomplete data. The median follow-up period was 11 months. Regarding the final histological diagnosis, pleomorphic adenoma was the most common and was identified in 153 patients. From an anatomical point of view, the caudal portion of the parotid was most often affected. Eighty-four patients presented with transient facial nerve paresis, and twelve developed permanent paralysis of the facial nerve or one of its branches, with the marginal mandibular branch being the most frequently involved.

In the first phase, a predictive model was created based on the predictors collected in the clinic, using the training data. The study used a supervised learning method. 80% of the cases were used to train the machine learning algorithms, and the remaining 20% were reserved for testing. An artificial neural network designed for tabular data was chosen for the analysis, with two hidden layers having, respectively, 200 and 100 neurons. The artificial neural network (ANN) processes categorical variables by embedding and applies a dropout layer before passing the input data to the linear layers, and continuous variables are subjected to batch normalisation.

Based on the performance of the ANN algorithm: (1) Patients with tumours located in the mid-portion of the gland, above the main trunk of the facial nerve, or in the superior area, above the frontal or orbital ramus, are at significant risk of facial nerve injury (FNI). (2) Histological type, especially pleomorphic adenoma, may lead surgeons to opt for a wider resection to reduce the risk of recurrence. (3) The volume of the tumour in the cephalo-caudal and anteroposterior axes requires a more extensive dissection of the branches of the facial nerve. (4) Age may influence recovery, with older patients typically having a slower recovery after FNI. (5) The need for a wider resection is also a risk factor.

4.7. Artificial Neural Network versus Multivariate Logistic Regression (LRM)– Results

In terms of diagnostic accuracy and prediction performance, the ANN model outperformed the LRM, achieving higher values for sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), area under the ROC curve (ROC–AUC), and overall accuracy. In the analysis of the factors that most influence the performance of the ANN models, the following were highlighted: tumour location in the gland (median, superior or deep lobe), tumour volume on the anteroposterior and cephalocaudal axes, histological type (pleomorphic adenoma), age and type of resection, all of which were significantly correlated with the risk of facial nerve injury. For the LRM model, the variables with the highest weight associated with the risk of facial nerve injury were the type of resection, location, sex and age. Artificial neural network (ANN) prediction models can be a valuable tool for both ENT–head and neck surgeons and patients, providing evidence-based estimates of the risk of facial nerve injury (FNI). An important advantage is the possibility of developing a computer that integrates clinical, radiological and histological or cytological data, thus facilitating more accurate patient counseling before surgery. (Chiesa-Estomba et al., 2020)

4.8. 3DPalsyNet: A Framework for Facial Palsy Grading and Motion Recognition Using Fully 3D Convolutional Neural Networks

This section provides a comprehensive experimental evaluation of the 3DPalsyNet framework, designed for both facial paralysis grading and mouth movement recognition. The tests were performed with PyTorch 0.4, on Windows 10, using an Nvidia GTX 1080 graphics card. 3DPalsyNet includes two main stages: the first stage focuses on video preprocessing, involving face detection and landmark location to identify the face in each frame of the sequence. In this step, the Deep Integrated Model is used. The detected face images are then cropped, and the number of

frames in each sequence is adjusted to a predetermined length. The second stage consists of two 3D convolutional neural networks, each dedicated to one of the facial analysis tasks.

Two datasets were used to evaluate the proposed method: the Extended Cohn-Kanade (CK+) and a dataset dedicated to facial paralysis. The CK+ dataset contains 593 sequences from 113 subjects, and the facial paralysis dataset contains 696 sequences from 17 subjects, collected from online sources. Since the CK+ sequences start with a neutral expression and end with a full one, they were adapted to the facial paralysis dataset by adding frames in reverse order, so that the last frame also represents a neutral expression. While all recordings in CK+ are made with controlled expressions, the facial paralysis dataset includes both directed movements and natural movements, such as speaking. For recognition of mouth movements, each sequence was labelled as one of four categories: no movement, smile, open mouth, or other types of movements. Using transfer learning from 3D CNNs pre-trained on the Kinetics dataset for general action recognition, the model was adapted for combined supervised learning, integrating the concepts of centre and softmax loss functions. 3DPalsyNet was evaluated on a dataset including individuals with varying degrees of facial palsy and variations in mouth movements, achieving notable classification accuracy: 82% for facial paralysis grading and 86% for mouth movement recognition. The impact of frame duration and loss function was analysed to evaluate the predictive ability of the proposed model. It was found that a shorter frame duration of eight units provides the best results for this task. Also, combining centre and softmax losses significantly improved the learning of spatiotemporal features, surpassing the performance of using the softmax loss alone, a fact also confirmed by previous research in the spatial domain. (Storey et al., 2019)

5. Clinical Study in Emergency County Hospital of Craiova

Parotid gland biopsies were obtained from a cohort of five patients who presented to the Oro-Maxillofacial Surgery Clinic of the Emergency County Hospital of Craiova. In most cases, the patients reported painful sensations and discomfort in the parotid region, which also exhibited significant swelling.

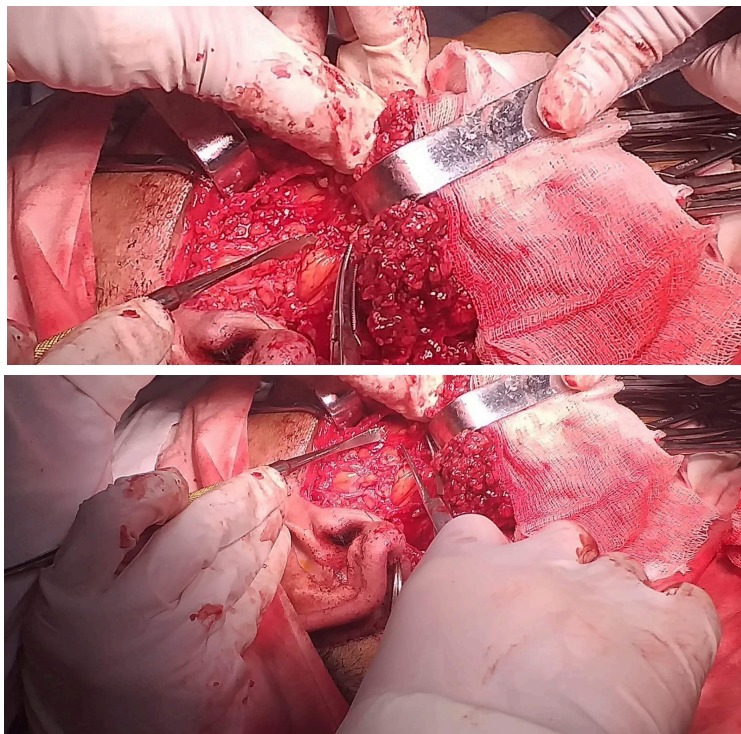


Figure 7. Intraoperative aspect of pleomorphic adenoma of the parotid gland

Figure 7 illustrates the intraoperative appearance of a pleomorphic adenoma of the parotid gland. The lesion is well circumscribed and located in the superficial lobe, showing small extensions. It has a gelatinous consistency and contains small hemorrhagic areas. The facial nerve is slightly displaced from its normal position.

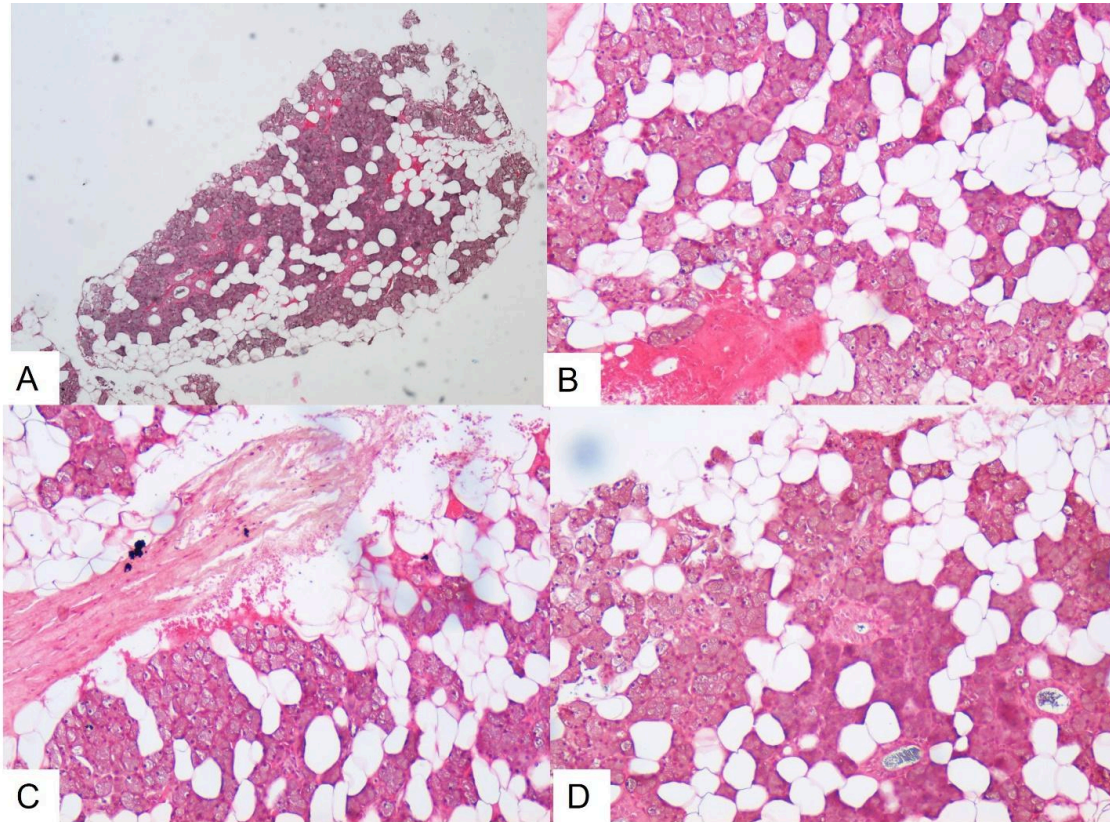


Figure 8. Parotid gland biopsy. Presence of unilocular adipocytes, predominantly epithelial component with myoepithelial cells, eosinophilic cytoplasm, hemorrhagic areas, and intensely eosinophilic stroma. The tumor capsule is incomplete. Stain hematoxylin-eosin.

Additionally, the patients expressed concern regarding their physical appearance, with noticeable facial asymmetry being observed. Two of the five patients also reported xerostomia. A particular case was represented by a pregnant patient in her third trimester who was diagnosed with this lesion. Management required an interdisciplinary team comprising a gynaecologist, a dentist, and an oral and maxillofacial surgeon. The patient underwent clinical and ultrasonographic evaluation (Iliescu et al., 2017) by the gynaecologist, who subsequently approved the surgical intervention in the parotid region.

The harvested tissues were fixed in 10% formalin for 48 hours, embedded in paraffin, sectioned using an automatic microtome, and subsequently stained with haematoxylin and eosin (H&E) for general histological evaluation in order to identify histopathological changes, as illustrated in Figure 8.

Pleomorphic adenoma of the parotid gland is a benign tumour with highly variable histopathological features, depending on the stage of the lesion. Although typically asymptomatic, if left untreated in its early stages, it carries a risk of malignant transformation. Additionally, it significantly impacts the patient's quality of life due to the development of pronounced facial asymmetry, which can lead to behavioural changes and anxiety disorders. In cases of large-volume tumours, facial nerve palsy may occur as a result of compression. Therefore, pleomorphic adenoma of the parotid gland requires a surgical approach, preferably at an early stage, involving either superficial or total parotidectomy.

6. Conclusions

Parotid gland tumours (PGT) are the most common salivary gland tumours and constitute approximately 2–6% of all head and neck neoplasms. Among benign tumours, the most common are pleomorphic adenoma (PA) and Warthin tumours, whereas mucoepidermoid carcinoma (MC) constitutes the most common malignant form. In most cases, tumours are located in the superficial lobe of the parotid gland.

The therapeutic strategy varies depending on the histological type: for benign tumours, enucleation or partial parotidectomy is recommended, while for malignant tumours, total parotidectomy or a more extensive surgical intervention is required. Establishing a reliable preoperative differential diagnosis before surgery is essential for choosing the treatment plan. Fine-needle aspiration biopsy can contribute to the diagnosis, but has limitations, such as insufficient amount of material, technical difficulties in deep lobe lesions, local infections and the risk of tumour dissemination. Imaging techniques are frequently used to establish the preoperative differential diagnosis and to precisely localise tumours. Although ultrasound and computed tomography (CT) can be used for this purpose, magnetic resonance imaging (MRI) is considered the most sensitive technique due to its high resolution for soft tissues. In addition to assessing the nature of the tumour mass, MRI allows identification of facial nerve involvement and its relationship to neighboring structures. Contrast-enhanced sequences are also useful for demonstrating perineural extension.

In recent years, advances in artificial intelligence have rapidly boosted the use of deep learning in medicine. This technology uses simple neurons integrated into a complex neural network. In the analysis and interpretation of medical images, deep learning methods can provide superior results than many traditional machine learning techniques.

From a practical application perspective, multiple studies have shown that artificial intelligence and deep learning methods can match, and sometimes even surpass, the performance of clinicians. Recent research has also shown that these techniques are comparable to the abilities of radiologists in detecting and segmenting lesions in MRI examinations. Radiomics is a new and promising technique that allows for the systematic quantification of tumours by extracting and analysing extensive texture information through high-throughput processes. With the rapid progress of algorithms, more and more research shows that radiomics supports the diagnosis, treatment, and prognostic assessment of tumours. The development, validation and comparison of various machine learning techniques are essential for the continued advancement and effective application of radiomics.

Imaging representation of tumours can provide important additional information to support clinical diagnosis. However, the deep learning (DL) model will not be able to completely replace biopsy evaluation in the near future, and much more data is needed before its widespread implementation in clinical practice. Comparison of diagnostic performance between physicians and the DL model demonstrated that it can provide accurate results, confirming its clinical utility.

As a state-of-the-art non-invasive modality, artificial intelligence (AI) has advanced capabilities in recognising patterns in imaging data and can provide quantitative assessments automatically. Numerous researchers have developed AI-based strategies to obtain relevant information, with the aim of increasing diagnostic accuracy and facilitating early detection of malignant tumours (Cumpătă, 2025).

Radiomics studies, in combination with deep learning techniques, have been applied to differentiate benign from malignant parotid gland lesions, using imaging data such as MRI, CT, conventional ultrasound, sonoelastography, diffusion imaging, dynamic contrast MR imaging, and susceptibility-weighted imaging.

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