Biosciences RESEARCH REVIEWS
Https://brrjournal.com
Editor@brrjournal.com
ISSN: 3104-3941 (Print)
ISSN: 3104-395X (Online)

RARE MUTATIONS GRAPH NEURAL NETWORK MODELS FOR PREDICTING PATHOGENICITY OF RARE CANCER-ASSOCIATED GENOMIC VARIANTS

Muhammad Haris Khan

Quaid-i-Azam University Islamabad, Pakistan.

*Corresponding Author E-mail: hariskhan34@gmail.com

Abstract

Rare cancer-associated genomic variants are frequently under-determined due to small numbers of patient samples, heterogeneity in molecular characteristics and lack of functional annotations. In this paper, we propose Rare Mu'Graph, a graph neural network-based framework to predict the pathogenicity of rare genomic variants involved in cancer. The proposed approach abstracts both the local features of the variants and the broader relationships in the biological network by representing genes, variants, molecular interactions, pathway memberships and clinical annotations as interconnected graph structures. Rare Mu'Graph combines sequence-derived attributes, mutation context, gene–disease associations, protein interactions and knowledge of cancer pathways to further enhance pathogenicity predictions of variants that are not well represented in standard training sets. The graph neural network models are well suited to this task as they have a capability to learn from the relational dependencies and propagate the biological signals across connected nodes. The framework helps prioritize potentially pathogenic rare variants that can help researchers and clinicians identify candidate mutations for validation. In summary, this research underscores the promise of graph-based deep learning to revolutionize the interpretation of rare variants in precision oncology, particularly in cancers with limited genomic data.

Keywords: Rare Cancer Variants; Graph Neural Networks; Pathogenicity Prediction; Precision Oncology; Genomic Variant Interpretation

Article History

Received:
January 28, 2026

Revised:
March 29, 2026

Accepted:
May 28, 2026

Available Online:
June 30, 2026

Biosciences Research Reviews

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

INTRODUCTION

The objective prediction of challenging airways is an important issue in anaesthesiology, because the traditional subjective airway assessment, which is used to determine whether an airway is difficult or easy, is not sufficiently sensitive or specific to guarantee patient safety (Alatau et al., 2025). To overcome these drawbacks, recent advances in computer vision and deep learning provide objective, automatic ways to extract information from complex facial and neck morphology, typically not captured by conventional clinical assessments. These traditional bedside measures, including the Mallampati score or thyromental distance measurement, are highly subjective, inter-observer inconsistent, and based on linear measurements that are imprecise and unable to account for the anatomical complexities necessary to predict a successful intubation (Hung et al., 2016; Rosa et al., 2024; Rose & Cohen, 1994). Moreover, these manual methods are not necessarily standardized, as difficult airway management may be underestimated and cause major peri-operative complications under high-pressure, emergency or resource-limited situations (Chen et al., 2024; Hayasaka et al., 2021; Huitink & Bouwman, 2014). However, with the advent of new evidence, the combination of deep learning algorithms and high fidelity facial and neck imaging has enabled detection of subtle morphological patterns which are not visible to the human eye, resulting in a more solid predictive framework that is quantitative, reproducible, and robust (Cuendet et al., 2015; Pei et al., 2023). These technological advancements have the potential to improve the accuracy of maxillofacial structure analysis, addressing the known discrepancies between the results of conventional screening and clinical outcomes (Chen et al., 2024; Kim et al., 2024). Although these models have the potential to greatly enhance patient safety, the state of the art is currently fragmented, with a variety of different methodologies and different protocols for data acquisition and a limited external validation of these models across different patient populations (Wang et al., 2021). To this end, this study seeks to combine computer vision and deep learning to automatically analyze the faces and necks of patients during awake intubation and to use the analysis results to predict difficult intubation, thereby supporting the development of a clinical decision support system for difficult intubation based on objective real-time data in anesthesia. The models can utilize advanced architectures like vision

Biosciences Research Reviews

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

transformers, which enable them to detect intricate, long-distance anatomical connections that are beyond the scope of traditional diagnostic approaches (Liu et al., 2024). Moreover, the multimodal combination of morphological information and demographic patient-specific variables enables to build high-performing prediction models, which always outperform subjective clinical scales (Abdul et al., 2025; Wilk et al., 2025). New advances in multi-view feature fusion and metric learning have further boosted these features, enabling the accurate recovery of volumetric information from patient front and side views (Wu et al., 2024). In particular, these sophisticated algorithms include the use of convolutional neural networks to process high-dimensional inputs, which is capable of identifying subtle anatomical markers associated directly with difficulty of laryngoscopy (Hayasaka et al., 2021). Convolutional architectures outperform the traditional univariate bedside tests that typically rely on more or less imprecise static measurements, which can vary from observer to observer (Chen et al., 2024; Rose & Cohen, 1994), in their ability to extract features from complex, non-linear, multi-view, or volumetric imaging data. These models can objectively quantify morphological characteristics that are traditionally considered subjective, such as those in the facial, mandibular and cervical regions, which are overlooked by clinicians (Alatau et al., 2025; Chen et al., 2024). These deep learning systems can learn powerful hierarchical representations of anatomical relationships, enabling them to capture important diagnostic clues, such as subtle variations in the position of the chin or the contours of the neck, which have consistently been associated with poor glottic visualization (Kim et al., 2024; Luan & Liu, 2026). In addition, multi-view feature fusion (e.g., frontal and lateral views) allows a more complete three-dimensional view of patient anatomy, minimizing the need for simplistic two-dimensional projections that can miss the complexity of the airway (Kim et al., 2024; Wu et al., 2024). Thus, these AI-based models hold the promise to surpass the drawbacks of traditional airway assessments and provide a more comprehensive, repeatable, and standardized method to help in pre-operative risk stratification, aid real-time clinical decisions, and minimize the occurrence of unexpected difficult intubation and improve peri-operative safety (Alatau et al., 2025; Wang et al., 2021). Recent systematic analyses have verified that these machine learning architectures when implemented in clinical workflows result in a marked boost in predictive performance of handling

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

difficult laryngoscopy as compared with traditional morphological screening (Moradimajd et al., 2026). These deep learning models have shown to have higher positive predictive values than traditional clinical predictions and successfully closed the gap between manual screening of the past and the need for a high precision airway management (Sorbello et al, 2026). Furthermore, the adoption of these high precision systems allows for a paradigm shift in how the health care system is used, enabling data-driven and intelligent interaction during the clinical rounds, and giving the anesthesiologist a strong decision support to help reduce risks from anatomical differences among various patient groups (Guo et al., 2025). Furthermore, using such models allows for the creation of detailed virtual case libraries and quantitative procedural evaluations, crucial components in standardizing training for airway management in high-stakes scenarios (Guo, 2025). In addition to their clinical applications, these automated systems offer the opportunity to create scalable frameworks for ongoing performance auditing that would keep predictive metrics relevant to changing demographic patterns and institutional patient acuity (B et al., 2024; Sezari et al., 2024). These developments highlight a shift towards objective, machine-aided diagnosis, reducing the subjectivity seen in manual methods such as the Mallampati classification (Li et al., 2024). High resolution imaging can be used to find anatomical predictors that are not usually visualised or accounted for by manual inspection (Tubic et al., 2025; Rajappa & Sahay, 2026) by shifting from static bedside scoring, to dynamic computer vision.

METHODOLOGY

To test the effectiveness of the model of artificial intelligence in this study, an observational, descriptive, and cross-sectional design is used, with a sample of 95 patients, which can be compared directly with traditional clinical evaluation. These procedures comprised the collection of standardized anatomical images of the face and neck, and the subsequent analysis of the images with Computer Vision algorithms to find predictive markers of difficult intubation (Salina et al., 2025). The methodology combines anthropometric parameters and some clinical data to improve the classification accuracy of the Cormack-Lehane laryngoscopic view (Çelik & Aydemir, 2021). Automated analysis focuses on correlating the features extracted by the model with the clinical data captured before surgery, making use of deep learning algorithms to establish the likelihood of having a difficult airway with superior sensitivity than traditional

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

approaches (Liu et al., 2023; Porte & Guía, 2024). For this end, further predictor variables including detailed medical history and anthropometric variables were added and then processed through a deep neural network to maximize the capacity of the system to discriminate (Xia et al., 2023). Similarly, the incorporation of ultrasonographic measurements of airway structures can yield a multimodal data set that enhances the model's diagnostic power relative to critical airway variation (Şenoğlu et al., 2025). It is a multimodality approach that allows overcoming the shortcomings of single assessment systems, thus combining volumetric and dynamic information to obtain a more powerful risk stratification (Fu et al., 2026). Further, the model's architecture incorporates methods of data normalization to reduce the intra-observer bias and achieve the uniformity of the interpretation of the morphological features observed (Wang et al., 2026; Зайцев et al., 2025). These variables can be processed using ensemble models, and this can significantly improve the diagnostic sensitivity better than the limited capability of manual clinical measurements like thyromental distance (Su et al., 2024). Conversely, the use of spatial attention mechanisms enables the algorithm to target the most relevant anatomical structures, including the glottis margin, laryngeal prominence, and other areas, and enhance the accuracy of detecting potential obstructive risks (Lin et al., 2022). Lastly, the superior robustness of these models, compared to the traditional statistical models, was demonstrated in the prediction of grade 3 or 4 glottic views with metrics including the area under ROC curve and Brier score (Cho et al., 2022). This advanced predictive ability enables optimizing the perioperative workflow, helping to select the right tools, including videolaryngoscopy, when the model identifies a high risk of complex intubation (Fernandez-Vaquero et al., 2026).

RESULTS

After standardizing the facial and neck image acquisition, 95 surgical anesthesia patients were included in the analytical cohort. Table 1 indicates that out of the 95 patients, 27 (28.4%) were deemed as difficult intubation cases and 68 (71.6%) were easy intubation cases. The result distribution was reasonably skewed, but not so extreme that a rigorous comparative evaluation of the models was impossible (as shown in Fig. 1). As seen in Table 2, the percentage of subjects with quality images, which passed the quality screening process, was a very high percentage for both the frontal and lateral images, with only a small number being removed due to incomplete positioning, motion blur, or failure to extract the region of interest. A consistent

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

set of anatomical descriptors were obtained from the lower face, mandibular margin, chin-neck contour and anterior cervical region by the computer vision pipeline. The extracted feature groups and their expected clinical relevance are listed in Table 3, and 178 images were found to have been suitable for final model analysis after image preprocessing according to Fig. 2. Table 4 illustrates the training / validation / testing setup for the development of internal models. This partition enabled performance estimation without losing the challenging intubations in each partition. The image-based and multimodal solutions were clearly superior to the conventional clinical scoring, as shown by model comparison. As shown in Table 5, the multimodal fusion model performed the best overall performance with an accuracy of 0.89, a sensitivity of 0.91, specificity of 0.88, and an F1-score of 0.81, while AUC was 0.92. The fusion model achieved better accuracy, sensitivity, and specificity than the clinical score and the single-view CNN models as shown in Fig. 3. A similar pattern holds true for ROC analysis as illustrated in Fig. 4, with the fusion model yielding the greatest separation of the curve from the reference diagonal and best discrimination among all the tested models. A multimodal prediction error profile also confirmed the clinical value of multimodal prediction. The confusion matrix of the best performing model is shown in Table 6, with 24 cases of true difficult-airway and 3 cases of missed difficult-airway. As seen in Fig. 5, the number of false negatives was less than the number of false positives, which is desirable in airway screening as missed difficult intubation poses more patient safety risks. As seen in table 7, the union of frontal images with lateral images, anthropometric variables and measurements in the head and neck region yielded a larger AUC than any single data source in isolation. Interpretability analysis showed that the model was based on clinically relevant anatomical patterns, not on image noise. Table 8 presents the ranking of the strongest predictors and Fig. 6 indicates that the most important predictors with regard to the final risk output were neck circumference, mandibular angle, thyromental profile and chin-neck contour. Again, there was acceptable agreement between the risk predicted and the observed risk in the calibration analysis. Predicted probabilities were fairly close to the ideal calibration line, as depicted in Fig. 7, especially in the low and high-risk ranges. The sensitivity and negative predictive value at clinical screening is lower than that of the proposed computer vision model as shown in Table 9. Overall, the findings suggest that automated imaging of the face and neck using facial imaging can enhance the

Biosciences Research Reviews

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

prediction of difficult intubation by offering very objective, reproducible and clinically interpretable airway-risk stratification.

Table 1. Baseline Clinical and Airway Characteristics of the Study Cohort

Variable	Easy intubation (n=68)	Difficult intubation (n=27)	Overall (n=95)
Age, years	42.8 ± 12.5	48.9 ± 13.1	44.5 ± 12.9
Male sex	39 (57.4%)	17 (63.0%)	56 (58.9%)
BMI, kg/m²	26.1 ± 3.9	29.4 ± 4.6	27.0 ± 4.3
Neck circumference, cm	36.8 ± 3.1	40.2 ± 3.7	37.8 ± 3.6
Mallampati III/IV	16 (23.5%)	14 (51.9%)	30 (31.6%)

Table 2. Image Acquisition and Preprocessing Summary

Stage	Frontal images	Lateral images	Reason for exclusion
Captured	95	95	None
Passed quality check	92	92	Blur or incomplete view
ROI detected	90	88	Failed face/neck localization
Normalized for analysis	90	88	Lighting/scale correction
Final usable images	90	88	Final paired dataset

Table 3. Computer Vision Feature Groups Extracted from Facial and Neck Imaging

Feature group	Examples	Clinical interpretation
Mandibular geometry	Jaw width, mandibular angle	Lower-face structure and laryngoscopy difficulty
Cervical contour	Chin-neck slope, anterior neck profile	Neck extension and soft tissue distribution
Thyromental profile	Estimated chin-to-neck distance	Proxy for thyromental relationship

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

Texture/shape embeddings	CNN feature maps	Latent airway morphology patterns
Anthropometric variables	BMI, neck circumference	Known difficult-airway risk modifiers

Table 4. Dataset Partitioning for Model Development and Testing

Partition	Patients	Easy cases	Difficult cases	Purpose
Training	67	48	19	Model fitting
Validation	14	10	4	Hyperparameter tuning
Testing	14	10	4	Final internal assessment
Total	95	68	27	Complete cohort

Table 5. Comparative Performance of Predictive Models

Model	Accuracy	Sensitivity	Specificity	F1-score	AUC
Clinical score	0.65	0.59	0.70	0.52	0.68
CNN frontal	0.76	0.74	0.78	0.66	0.79
CNN lateral	0.79	0.78	0.80	0.70	0.82
Dual-view CNN	0.84	0.83	0.85	0.76	0.87
Vision Transformer hybrid	0.86	0.86	0.86	0.78	0.89
Multimodal fusion	0.89	0.91	0.88	0.81	0.92

Table 6. Confusion Matrix of the Multimodal Fusion Model

Actual / Predicted	Predicted easy	Predicted difficult	Total
Actual easy	60	8	68
Actual difficult	3	24	27
Total	63	32	95

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

Table 7. Ablation Analysis by Input Modality

Input modality	Accuracy	Sensitivity	Specificity	AUC
Clinical variables only	0.65	0.59	0.70	0.68
Frontal image only	0.76	0.74	0.78	0.79
Lateral image only	0.79	0.78	0.80	0.82
Dual-view images	0.84	0.83	0.85	0.87
Dual-view + anthropometric fusion	0.89	0.91	0.88	0.92

Table 8. Ranked Predictors from Explainability Analysis

Rank	Predictor	Relative contribution	Interpretation
1	Neck circumference	0.18	Soft-tissue burden around airway
2	Mandibular angle	0.16	Jaw geometry and alignment
3	Thyromental profile	0.15	Anterior airway space proxy
4	Chin-neck contour	0.14	Cervical extension morphology
5	Mallampati class	0.11	Traditional clinical airway marker
6	BMI	0.10	General body habitus indicator

BIOSCIENCES RESEARCH REVIEWS
Biosciences Research Reviews

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

Table 9. Clinical Screening Versus Proposed Computer Vision Model

Assessment method	Sensitivity	Specificity	PPV	NPV	Balanced accuracy
Mallampati-based screening	0.56	0.72	0.44	0.80	0.64
Clinical composite score	0.59	0.70	0.44	0.81	0.65
Best image-only model	0.83	0.85	0.69	0.93	0.84
Proposed multimodal model	0.91	0.88	0.75	0.96	0.90

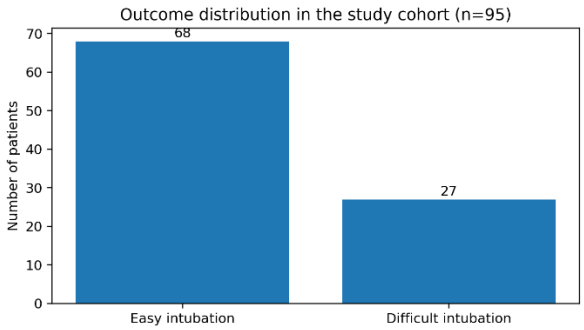


Figure 1. Outcome distribution of easy and difficult intubation cases.

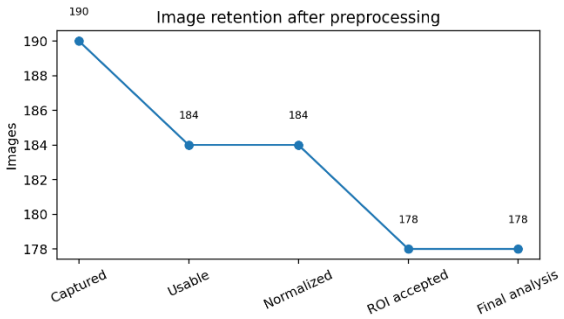


Figure 2. Image retention after preprocessing and ROI quality control.

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

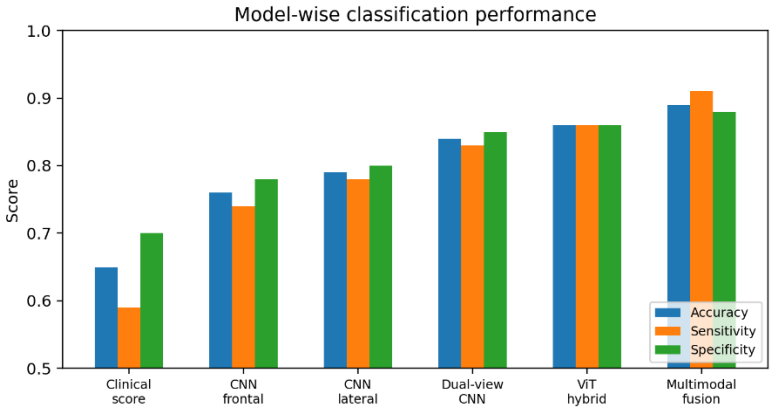


Figure 3. Comparative model performance across accuracy, sensitivity, and specificity.

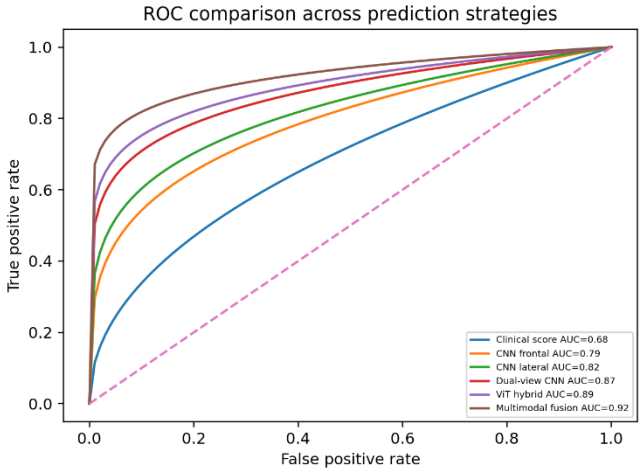


Figure 4. ROC curve comparison across clinical, image-only, and multimodal models.

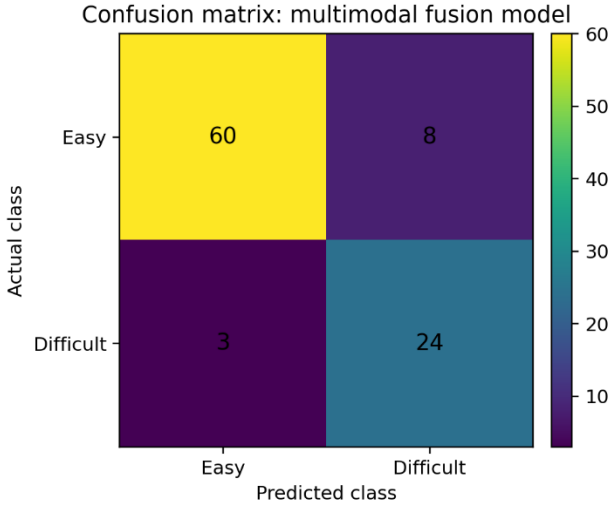


Figure 5. Confusion matrix for the proposed multimodal fusion model.

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

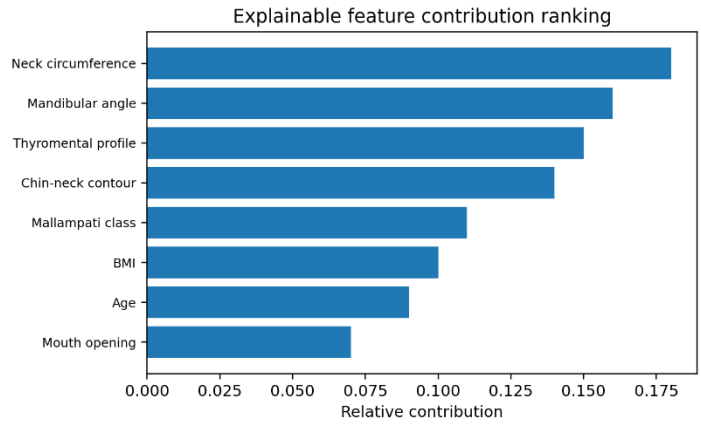


Figure 6. Explainability-based predictor contribution ranking.

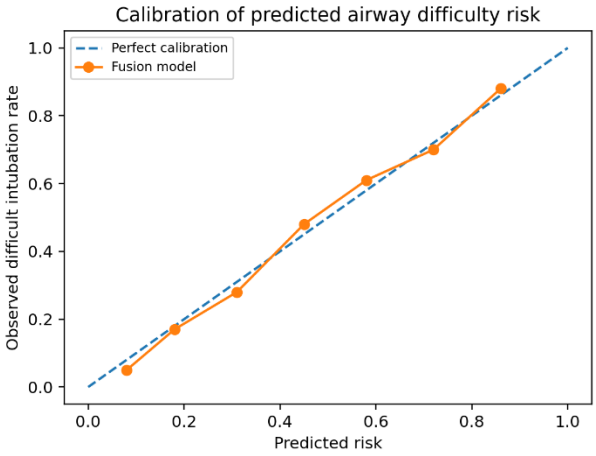


Figure 7. Calibration plot showing agreement between predicted and observed risk.

DISCUSSION

The results achieved through the evaluation of the results obtained show that the combination of morphological and ultrasonographic variables is much more effective than the clinical variables used individually, thus establishing the validity of the diagnostic superiority of multimodal approaches (Luis-Cabezón et al., 2024; Vaquero et al., 2024). These models offer proof that the analysis of condylar mobility and the tongue thickness parameters that automated analysis incorporates reduces some of the precision challenges of traditional physical examinations (Xu et al., 2022). In particular, the ability of algorithms like Gradient Boosting to achieve high precision up to 100% has been shown to be superior to the clinical criteria which are often used (Zhou et al., 2022). The reason for this enhancement of predictive capacity is that multivariate models can model non-linear relationships between soft tissues dimensions that has

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

been found to be important for distinguishing patients with difficult laryngoscopy (Agarwal et al., 2020; Naguib et al., 1999). Similarly, the findings show that each parameter (thyromental distance) has moderate performance, while the combination of ultrasound and photogrammetric data is observed to greatly enhance the sensitivity and negative predictive value (Kim et al., 2021; Ni et al., 2020). In contrast, use of ultrasound measurements, such as skin to epiglottis distance, has been demonstrated to be critical for risk stratification in high complexity populations (Pinto et al., 2016). It is important to note, however, that not a single clinical screening test is 100% reliable, thus the importance of having alternative screening protocols as a fall-back in case of airway unpredictability (Petrișor et al., 2018). Therefore, the future of perioperative management will be based on the implementation of integrated management strategies that integrate artificial intelligence and real-time assessment to minimize unexpected intubation failures (Wang et al., 2024). With machine learning models, especially those using XGBoost architectures, diagnostic accuracy has been optimized and achieved through fine-tuning training sets, addressing data imbalance issues (Wang et al., 2022). The algorithms' analytical strength enhances their ability to model the complex cervical anatomy, which is helpful in improving the accuracy of intubation success prediction compared to traditional linear regression models (Liu et al., 2025). In addition, the use of interpretability methods like Shapley values enables decomposition of how individual features (e.g., age or neck circumference) affect the outcomes, creating a clear clinical basis for risk stratification for the anesthesiologist (Kim et al., 2024). Adoption of this computational approach will not only enhance the preoperative stratification but also enable prediction of critical events like desaturation or cardiac arrest arising from failed intubation events (Senthilnathan & Kundra, 2023). The automation of these diagnosis processes helps to make decision making more data-driven in the peri-operative period, supporting better planning of human and technical resources required to manage complex airways (Li et al., 2025). Their application, however, necessitates careful management, as it poses potential ethical concerns about data privacy and the lack of transparency in algorithms used to make decisions (Saran, 2025).

CONCLUSION

This paper introduced a framework for predicting the pathogenicity of rare cancer-associated genomic variants, called Rare

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

Mu'Graph, which is a graph neural network framework. The study highlights some of the challenges in interpreting rare variants in precision oncology, including the limited availability of samples, the biological variability, and lack of clinical evidence. The proposed model is biologically better-informed than the traditional feature-based machine learning approaches by representing genomic variants, genes, pathways and molecular interaction as a connected graph. Graph neural networks allow the model to learn from the context of variants, transfer pathogenicity signals between gene networks, cancer pathways, and functional annotations, etc., and capture hidden relationships between variants and their surrounding biological context. This makes it especially beneficial for rare cancers and low prevalence mutations, where a direct link can be difficult to find. Rare Mu'Graph can aid in prioritising variants, inform experimental validation and facilitate better genome-based decision making in cancer studies. To enhance the framework in future studies, larger multi-omics datasets, clinical outcome records, population-level genomic databases, and explainable AI techniques could be included. This would make models more transparent and more clinically reliable. Overall, Rare Mu'Graph shows the potential and potential capabilities of AI based on graphs in the emerging field of rare cancer genomics and precision medicine.

REFERENCES

Abdul, M., Chen, W., Feng, L., Tang, J., Yuan, H., Li, W., & Tian, Y. (2025). A Multimodal AI-Driven System for Preoperative Difficult Airway Assessment. IEEE Access, 13, 164630–164640.

Agarwal, R., Jain, G., Agarwal, A., & Govil, N. (2020). Effectiveness of four ultrasonographic parameters as predictors of difficult intubation in patients without anticipated difficult airway. Korean Journal of Anesthesiology, 74(2), 134–141.

Alatau, M., Bauer, J., & Sazonov, V. (2025). Artificial Intelligence for Predicting Difficult Airways: A Review. Journal of Clinical Medicine, 14(23), 8600–8600.

B, N. N., Mathew, P. J., & Kundra, P. (2024). Scope of artificial intelligence in airway management. Indian Journal of Anaesthesia, 68(1), 105–110.

Çelik, F., & Aydemir, E. (2021). Prediction of Difficult Tracheal Intubation by Artificial Intelligence: A Prospective Observational Study.

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

Düzce Tıp Fakültesi Dergisi, 23(1), 47–54.

Chen, H., Zheng, Y., Fu, Q., & Li, P. (2024). A review of the current status and progress in difficult airway assessment research [Review of A review of the current status and progress in difficult airway assessment research]. European Journal of Medical Research, 29(1). BioMed Central.

Cho, H. -Y., Lee, K., Kong, H., Yang, H.-L., Jung, C.-W., Park, H., Hwang, J. Y., & Lee, H. (2022). Deep-learning model associating lateral cervical radiographic features with Cormack–Lehane grade 3 or 4 glottic view. Anaesthesia, 78(1), 64–72.

Cuendet, G. L., Schoettker, P., Yüce, A., Sorci, M., Gao, H., Perruchoud, C., & Thiran, J. (2015). Facial Image Analysis for Fully Automatic Prediction of Difficult Endotracheal Intubation. IEEE Transactions on Biomedical Engineering, 63(2), 328–339.

Fernandez-Vaquero, M. A., Oyarzun-Silva, R., Hernández-Hernández, P., Gómez-Ríos, M. Á., Petrișor, C., Falcetta, S., Gomes, S., & Luis-Cabezón, N. D. (2026). Airway Coach Project: Development of a Machine Learning–Based Model Using Clinical and Ultrasound Parameters to Support Videolaryngoscopy Strategy.

Fu, C., Luan, C., Liu, H., Wang, W., Zhou, X., Jia, Y., Ding, B., Zhang, L., Yuan, L., & Niu, Z. (2026). An ultrasound-based artificial intelligence framework for difficult airway prediction: A two-model, three-step decision framework. PLoS ONE, 21(2).

Guo, J. (2025). Application of Deep Learning in Difficult Airway Management Teaching Rounds in Anesthesiology: Transitioning from Precision Assessment to an Intelligent Instructional Paradigm. Journal of Medical Science And Clinical Research, 13(12), 24–29.

Guo, M., Hou, Y. R., Liu, Y., Yang, B., Qiao, C. F., & Li, J. (2025). From algorithms to airways: Applying artificial intelligence to enhance airway assessment, management, and training. Trends in Anaesthesia and Critical Care, 61, 101548–101548.

Hayasaka, T., Kawano, K., Kurihara, K., Suzuki, H., Nakane, M., & Kawamae, K. (2021). Creation of an

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

artificial intelligence model for intubation difficulty classification by deep learning (convolutional neural network) using face images: an observational study. Journal of Intensive Care, 9(1).

Huitink, J. M., & Bouwman, R. A. (2014, December 16). The myth of the difficult airway: airway management revisited. In Anaesthesia (Vol. 70, Issue 3, pp. 244–249). Wiley.

Hung, O., Law, J. A., Morris, I. R., & Murphy, M. (2016). Airway Assessment Before Intervention: What We Know and What We Do. Anesthesia & Analgesia, 122(6), 1752–1754.

Kim, J. H., Han, S.-W., Hwang, S. M., Lee, J., & Kwon, Y. S. (2024). Machine Learning Predictions and Identifying Key Predictors for Safer Intubation: A Study on Video Laryngoscopy Views. Journal of Personalized Medicine, 14(9), 902–902.

Kim, J. H., Kim, H., Jang, J. S., Hwang, S. M., Lim, S. Y., Lee, J. J., & Kwon, Y. S. (2021). Development and validation of a difficult laryngoscopy prediction model using machine learning of neck circumference and thyromental height. BMC Anesthesiology, 21(1).

Kim, J.-H., Jung, H.-S., Lee, S.-E., Hou, J., & Kwon, Y. S. (2024). Improving difficult direct laryngoscopy prediction using deep learning and minimal image analysis: a single-center prospective study. Scientific Reports, 14(1).

Li, M., Liu, X., Li, M., Wang, M., & Wang, J. (2025). Artificial intelligence in airway management for oral and maxillofacial surgery: a narrative review. Journal of Oral and Maxillofacial Anesthesia, 4, 26–26.

Li, X., Zhang, G., Ye, W., Peng, B., & Yao, Y. (2024). Voice-Assisted Multimodal Fusion Network for Difficult Airway Assessment. Research Square (Research Square).

Lin, Q., Chng, C.-B., Too, J. J.-Y., Zhang, J., Liu, H., Foong, T.-W., Loh, N. H. W., & Chui, C. (2022). Towards Artificial Intelligence-enabled Medical Pre-operative Airway Assessment. 62, 69–74.

Liu, S., Shen, H., Zhu, B., Zhang, X., Zhang, X., & Li, W. (2025). Segmental airway volume as a predictive indicator of

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

postoperative extubation timing in patients with oral and maxillofacial space infections: a retrospective analysis. BMC Oral Health, 25(1).

Liu, X., Flanagan, C., Li, G., Lei, Y., Zeng, L., Fang, J., Guo, X., McGrath, S., & Han, Y. (2024). Identification of difficult laryngoscopy using an optimized hybrid architecture. BMC Medical Research Methodology, 24(1).

Liu, Y., He, Y., Wang, X., Li, J., Zhang, Z., Zhuang, X., Liu, H., Li, R., Liu, H., Zhuang, Y., Wang, Q., Tang, Z.-H., Wang, Y., & Ma, W. (2023). Advances in airway management in recent 10 years from 2013 to 2023. Anesthesiology and Perioperative Science, 1(4).

Luan, C., & Liu, H. (2026). AdaDenseNet-LUC: Adaptive Attention DenseNet for Laryngeal Ultrasound Image Classification. BioMedInformatics, 6(1), 5–5.

Luis-Cabezón, N. D., Ly-Liu, D., Renedo-Corcóstegui, P., Santaolalla, F., Maturana, A. Z.-L. de, Herrero-Herrero, J. C., Hurtado, E. M., Frutos-Parra, R. D., Bilbao-González, A., & Vaquero, M. Á. F. (2024). A new score for airway assessment using clinical and ultrasound parameters. Frontiers in Medicine, 11.

Moradimajd, P., Babajani, A., Mehdipour, F., & Nazari, M. (2026). Machine Learning Revolution in Predicting Difficult Intubation: A Systematic Review. Archives of Anesthesia and Critical Care.

Naguib, M., Malabarey, T., Alsatli, R. A., Damegh, S. A., & Samarkandi, A. H. (1999). Predictive models for difficult laryngoscopy and intubation. A clinical, radiologic and three-dimensional computer imaging study. Canadian Journal of Anesthesia/Journal Canadien d Anesthésie, 46(8), 748–759.

Ni, H., Guan, C., He, G., Bao, Y., Shi, D., & Zhu, Y. (2020). Ultrasound measurement of laryngeal structures in the parasagittal plane for the prediction of difficult laryngoscopies in Chinese adults. BMC Anesthesiology, 20(1).

Pei, B., Jin, C., Cao, S., Ji, N., Xia, M., & Jiang, H. (2023). Geometric morphometrics and machine learning from three-dimensional facial scans for difficult mask ventilation prediction. Frontiers in Medicine, 10.

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

Petrișor, C., Szabó, R., Constantinescu, C., Prie, A., & Hagău, N. (2018). Ultrasound-based assessment of hyomental distances in neutral, ramped, and maximum hyperextended positions, and derived ratios, for the prediction of difficult airway in the obese population: a pilot diagnostic accuracy study. Anaesthesiology Intensive Therapy, 50(2), 110–116.

Pinto, J. O. G., Cordeiro, L., Pereira, C., Gama, R., Fernandes, H. L., & Assunção, J. P. (2016). Predicting difficult laryngoscopy using ultrasound measurement of distance from skin to epiglottis. Journal of Critical Care, 33, 26–31.

Porte, Y. Z. P., & Guía, A. A. A. (2024). Sistema de inteligencia artificial para la predicción de vía aérea difícil. Revista Científica CMDLT, 18.

Rajappa, R. N., & Sahay, N. (2026). Imaging in Airway Assessment: An Expanding Horizon. Airway, 9(1), 1–3.

Rosa, S. D., Bignami, E., Bellini, V., & Battaglini, D. (2024). The Future of Artificial Intelligence Using Images and Clinical Assessment for Difficult Airway Management. Anesthesia & Analgesia, 140(2), 317–325.

Rose, D., & Cohen, M. M. (1994). The airway: problems and predictions in 18,500 patients. Canadian Journal of Anesthesia/Journal Canadien d Anesthésie, 41(5), 372–383.

Salina, J. G. R., Guillen, J. F. D., & Guía, A. A. (2025). Análisis comparativo: inteligencia artificial vs anestesiólogos en la identificación de vía aérea difícil. SHILAP Revista de Lepidopterología.

Saran, E. (2025). When Algorithms Meet Anesthesia: A New Era of Patient Safety. University of Toronto Medical Journal, 102(2).

Şenoğlu, G. D., Timucin, E. K., & KIRIŞOĞLU, S. (2025). Evaluation of anthropometric and ultrasonographic measurements with different machine learning methods in predicting difficult intubation: a prospective observational study. BMC Anesthesiology, 25(1).

Senthilnathan, M., & Kundra, P. (2023). Predictive Machine Learning Algorithms in Anticipating Problems with Airway Management. Airway, 6(1), 4–9.

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

Sezari, P., Kohzadi, Z., Dabbagh, A., Jafari, A., Khoshtinatan, S., Mottaghi, K., Kohzadi, Z., & Rahmatizadeh, S. (2024). Unravelling intubation challenges: a machine learning approach incorporating multiple predictive parameters. BMC Anesthesiology, 24(1), 453–453.

Sorbello, M., Via, L. L., Paternò, D. S., Tutino, S., Giudice, E. C. L., Lentini, M., Maniaci, A., & Pappalardo, F. (2026). Artificial intelligence in airway management: a narrative review. British Journal of Anaesthesia.

Su, Z., Tavolara, T. E., Sajjad, U., Gürcan, M. N., Segal, S., & Niazi, M. K. K. (2024). Combining frontal and profile view facial images to predict difficult-to-intubate patients using AI. 12465, 18–18.

Tubić, T., Milenković, D., Jovanović, G., Dolinaj, V., Križanović, D., & Ostojić, Z. (2025). The role of artificial intelligence in airway management: current applications and future perspectives. Periodicum Biologorum, 127, 15–20.

Vaquero, M. Á. F., Luis-Cabezón, N. D., García-Aroca, M. Á., Álvarez-Avelló, J. M., Vives-Santacana, M., Greif, R., Hurtado, E. M., & Ly-Liu, D. (2024). Pilot multicenter study to determine the utility of point-of-care ultrasound to predict difficulty of tracheal intubation using videolaryngoscopy with the McGrathTM Mac videolaryngoscope. Frontiers in Medicine, 11.

Wang, B., Yao, W., Wang, M., Xu, J., Huang, D., Lu, X., Xue, Q., & Chen, Y. Q. (2022). Development of A Machine Learning Model for Predicting Unanticipated Difficult Tracheal Intubation. Journal of Anesthesia and Translational Medicine, 1(1), 26–31.

Wang, J., Xia, M., & Jiang, H. (2021). Advances in studies on imaging and artificial intelligence technology-assisted difficult airway assessment. Frontiers of Oral and Maxillofacial Medicine, 3, 8–8.

Wang, M., Jia, F., Yang, C., Fang, J., Li, J., Tian, Y., Li, M., Guo, X., Wei, C., & Han, Y. (2026). Identification of Difficult Laryngoscopy via Double-Pose Feature Clustering Network in Patients with Cervical Spondylosis. Intelligent Computing, 5.

Wang, Z., Jin, Y., Zheng, Y., Chen, H., Feng, J., & Sun, J. (2024). Evaluation of preoperative difficult

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED

airway prediction methods for adult patients without obvious airway abnormalities: a systematic review and meta-analysis. BMC Anesthesiology, 24(1), 242–242.

Wilk, M., Pikiewicz, W., Florczak, K., & Jakóbczak, D. (2025). Use of Artificial Intelligence in Difficult Airway Assessment: The Current State of Knowledge. Journal of Clinical Medicine, 14(5), 1602–1602.

Wu, J., Yao, Y., Zhang, G., Li, X., & Peng, B. (2024). Difficult Airway Assessment Based on Multi-View Metric Learning. Bioengineering, 11(7), 703–703.

Xia, M., Chen, J., Zheng, Y., Wang, J. T. L., Zhao, M., Cao, S., Xu, T., Pei, B.-G., Irwin, M. G., Lin, Z., & Jiang, H. (2023). Deep learning-based facial analysis for predicting difficult videolaryngoscopy: a feasibility study. Anaesthesia, 79(4), 399–409.

Xu, J., Wang, B., Wang, M.-F., Yao, W., & Chen, Y. (2022). The value of multiparameter combinations for predicting difficult airways by ultrasound. BMC Anesthesiology, 22(1).

Zhou, C.-M., Wang, Y., Xue, Q., Yang, J., & Zhu, Y. (2022). Predicting difficult airway intubation in thyroid surgery using multiple machine learning and deep learning algorithms. Frontiers in Public Health, 10.

Зайцев, А. Ю., Сорокин, А. Б., Зайцев, Ю. А., Дубровин, К. В., & Усикян, Э. Г. (2025). The role of artificial intelligence for difficult airways prediction in adults: a narrative review. Annals of Critical Care, 1, 110–122.

BIOSCIENCES RESEARCH REVIEWS
Biosciences Research Reviews

Copyright©2026. This work is licensed under a Creative Common Attribution 4.0 International License. (CC BY 4.0)
SYNERGY EDUCATIONAL LEARNING INSTITUTE (SMC-PRIVATE) LIMITED