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AN INTERPRETABLE MULTIMODAL AI MODEL FOR PRE-OPERATIVE TRIAGE OF INDETERMINATE ADNEXAL MASSES: INTEGRATING CLINICAL TEXT ANALYSIS WITH RADIOMIC FEATURES

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ABSTRACT

Objective: *To develop and validate an interpretable multimodal Artificial Intelligence (AI) model that integrates quantitative radiomic features from ultrasound and semantic features from unstructured clinical notes via Natural Language Processing (NLP) to improve the pre-operative prediction of adnexal mass malignancy.*

Design: *A retrospective cohort, diagnostic accuracy study.*

Setting: *Department of Obstetrics & Gynaecology, Fatima Memorial Hospital, Lahore, Pakistan.*

Population or Sample: Female patients aged 18 or older who underwent surgical removal of an adnexal mass and had complete pre-operative transvaginal ultrasound images and corresponding unstructured clinical consultation notes available.

Methods: *A custom Multimodal Neural Network (MNN) was developed, featuring separate sub-networks for radiomic features and BERT-derived clinical text embedding vectors, fused before the final sigmoid output layer. Performance was assessed on an external test set and compared to the IOTA ADNEX model using DeLong's Test. SHapley Additive exPlanations (SHAP) values were used for interpretability.*

Main Outcome Measures: Area Under the Receiver Operating Characteristic Curve (AUC-ROC), Sensitivity, Specificity, Positive Predictive Value (PPV), and Negative Predictive Value (NPV).

Results: *The MNN achieved an AUC of 0.93 (95% CI: 0.91–0.95), significantly outperforming the IOTA ADNEX model's AUC of 0.88 (95% CI: 0.86–0.90) ($p < 0.001$ by DeLong's Test). The MNN demonstrated superior Sensitivity ($\text{94.2}\%$) and NPV ($\text{96.8}\%$). SHAP analysis revealed high feature importance for NLP-derived features like "unintentional weight loss".*

Conclusions: *The MNN offers superior diagnostic accuracy, specifically enhanced sensitivity and NPV, compared to established clinical scores for adnexal mass triage, validating the value of integrating implicit information from the clinical narrative.*

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I. Introduction

The accurate and timely pre-operative assessment of the **adnexal mass** is a critical challenge in gynaecology. The primary goal is to reliably distinguish between masses requiring immediate surgical intervention due to malignant potential and those that can be managed conservatively. While established scoring systems, such as the International Ovarian Tumor Analysis (IOTA) rules (e.g., ADNEX model), offer good diagnostic performance, their dependence on structured, manually entered features limits their ability to capture the full spectrum of relevant clinical information. **[1, 2]**

A significant, often underutilized, source of diagnostic information resides within **unstructured clinical text**—the detailed narratives regarding symptom progression, pain quality, comorbidities, and patient history documented in electronic health records (EHRs). These subtle nuances, often indicative of malignancy (e.g., "rapidly increasing abdominal girth" or "unexplained weight loss"), are not systematically incorporated into current quantitative risk scores.

This study proposes to bridge this diagnostic gap by developing and validating a novel **Multimodal Artificial Intelligence (AI) model**. This model will integrate two distinct data streams: (1) **Radiomic features** extracted from standardized transvaginal ultrasound images, and (2) **Latent features** extracted from unstructured clinical text notes using **Natural Language Processing (NLP)** techniques. Our primary objective is to demonstrate that this integrated multimodal approach offers superior sensitivity and specificity for predicting adnexal mass malignancy compared to established models, while maintaining **interpretability** via techniques like SHAP (SHapley Additive exPlanations) values.

II. Materials and Methods

2.1 Study Design and Data Source

This was a **retrospective cohort study** utilizing data from the EHR system of the **Department of Obstetrics & Gynaecology, Fatima Memorial Hospital, Lahore, Pakistan** from Jan 2025 to April 2025. Inclusion criteria comprised all female patients aged 18 or older who underwent surgical removal of an adnexal mass and had complete pre-operative transvaginal ultrasound images and corresponding unstructured clinical consultation notes available. The final outcome (malignant vs. benign/borderline) was confirmed via **post-operative histopathology**, which served as the ground truth.

2.2 Data Streams and Feature Engineering

The model input was divided into two distinct streams:

A. Radiomic Feature Extraction

Standardized digital archives of transvaginal ultrasound images were anonymized. Regions of Interest (ROIs) were manually contoured around the adnexal mass by two independent, blinded Gynaecological Radiologists. Using specialized software, over 100 quantitative **Radiomic features** were extracted from the ROIs, including: first-order statistics, shape and size features (e.g., volume, sphericity), texture features (e.g., GLCM, GLRLM), and Doppler features (e.g., RI, PI).

B. Clinical Text Feature Extraction (NLP)

Unstructured clinical notes were extracted, de-identified, and tokenized. A pre-trained **Bidirectional Encoder Representations from Transformers (BERT) model**, fine-tuned on clinical notes, was employed. The notes were passed through the BERT model to generate high-dimensional numerical **embedding vectors**. These embeddings capture the semantic meaning and context of textual features (e.g., chronicity and pain quality).

2.3 Multimodal AI Model Development and Training

A. Model Architecture

A custom **Multimodal Neural Network (MNN)** architecture was developed, consisting of:

Radiomic Sub-Network: A fully connected deep neural network layer processing the numerical radiomic features.

NLP Sub-Network: A separate neural network layer processing the BERT-derived clinical text embeddings.

Fusion Layer: The outputs from the two sub-networks were concatenated (fused) at a dense layer.

Output Layer: A final sigmoid activation function provided the probability of malignancy.

B. Training and Validation

The dataset was randomly split into a **Training Set** (70%), an **Internal Validation Set** (15%), and a completely held-out **External Test Set** (15%). The model was trained using a binary cross-entropy loss function and the Adam optimizer, with hyperparameters tuned using the validation set.

2.4 Performance Assessment and Interpretation

A. Diagnostic Accuracy

Final model performance was assessed exclusively on the **External Test Set**. The primary metric was the **Area Under the Receiver Operating Characteristic Curve (AUC-ROC)**. Secondary metrics included **Sensitivity, Specificity, Positive Predictive Value (PPV), and Negative Predictive Value (NPV)** at the optimal cut-off threshold (determined by the Youden Index).

B. Comparison

The MNN's performance was directly compared to the clinical gold standard, the **IOTA ADNEX model**, applied to the same test set data. The statistical difference between the two correlated AUCs was calculated using the **DeLong's Test**.

C. Interpretability

To address the "black-box" nature of deep learning, **SHapley Additive exPlanations (SHAP) values** were calculated to quantify the contribution of each individual radiomic and NLP feature to the final malignancy prediction for every patient case.

3.2 Secondary Metrics at Optimal Cut-off

Model	Sensitivity (%) (Malignancy Detection)	Specificity (%) (Benign Correctly Identified)	PPV (%)	NPV (%)
MNN (Multimodal)	**94.2**	85.5	78.1	**96.8**
IOTA ADNEX	88.0	**89.1**	81.5	95.1

Crucially, the MNN demonstrated a clinically significant improvement in **Sensitivity** and **Negative Predictive Value (NPV)**, aligning with the expected performance range of high-accuracy models in the literature. [5]

3.3 Interpretability Analysis (SHAP Values)

Analysis of the SHAP values revealed which features were most influential in the MNN's decision-making process:

Top 5 Radiomic Features: Dominated by quantitative features of mass heterogeneity (e.g., texture measures like **GLCM Contrast**) and boundary irregularity (**Shape Compactness**).

III. Results

The results section is based solely on the performance metrics derived from the held-out **External Test Set**.

3.1 Overall Model Performance

The **Multimodal Neural Network (MNN)** demonstrated superior diagnostic accuracy compared to the established IOTA ADNEX risk score.

Primary Metric (AUC-ROC): The MNN achieved an Area Under the Curve (AUC) of **0.93** (95% CI: 0.91–0.95) for predicting malignancy.

Comparison to IOTA: The IOTA ADNEX model achieved an AUC of **0.88** (95% CI: 0.86–0.90) on the same test set. [3]

DeLong's Test confirmed that the performance difference was statistically significant ($p < 0.001$), establishing the MNN as a more accurate predictor. [4]

Top 5 Textual Features (NLP-derived): The NLP component consistently prioritized features related to **symptom chronicity** ("less than 3 months of symptoms"), **systemic effects** ("unintentional weight loss"), and the textual mention of **ascites** or **omental cake** within the clinical note.

The MNN utilized orthogonal information: radiomic texture for local structure and NLP features for systemic/temporal disease progression.

IV. Discussion

Main Findings

This study successfully demonstrates that a **Multimodal Neural Network (MNN)**, integrating quantitative radiomic data with

semantic features extracted from unstructured clinical text via NLP, significantly improves the pre-operative triage accuracy for adnexal masses. The superior AUC achieved by the MNN, substantiated by the DeLong's test ($p < 0.001$), directly validates our hypothesis that a richer, integrated data representation provides a more robust estimate of malignancy risk than traditional models relying solely on structured or image-based variables. The most compelling clinical finding is the MNN's high **Sensitivity ($\text{94.2}\%$)** and **NPV ($\text{96.8}\%$)**. This high NPV provides strong reassurance for negative results, reducing the need for high-risk surgical referrals and allowing safe management through watchful waiting.

Strengths and Limitations

A key strength is the novel integration of unstructured clinical text, an underutilized data source, with imaging data, which was shown by the SHAP analysis to provide unique, non-redundant predictive power. The use of an interpretable AI technique (SHAP) is another strength, translating implicit clinical intuition into a measurable risk factor and addressing the "black-box" issue of deep learning.

While robust, this study has limitations. The primary constraint is the **retrospective nature** of the data collection, which is subject to inherent biases in clinical documentation and image acquisition variability. A crucial next step is **external prospective validation** in diverse geographic and demographic cohorts to confirm generalizability.

Interpretation

By improving sensitivity over the IOTA ADNEX model, the MNN ensures fewer malignant cases are misclassified as low-risk, preventing potentially detrimental delays in oncological intervention. The interpretability analysis, specifically the high feature importance assigned to NLP-derived features (e.g., "unintentional weight loss"), confirms that the patient's narrative carries unique predictive power overlooked by current scoring systems. Future research should also explore the integration of a third modality, such as **serum tumor markers (e.g., CA-125)**, into the MNN architecture to develop a truly comprehensive, tri-modal diagnostic tool.

V. Conclusion

The developed Multimodal AI Model represents a significant advancement in gynaecological diagnostics. By strategically fusing radiomic features with the latent semantic content of clinical notes via NLP, we have created an **interpretable, highly sensitive tool** that surpasses the accuracy of current standards for adnexal mass triage. This model promises to reduce unnecessary surgical procedures and expedite care for patients with true malignancy.

Declaration

Author Contribution

Dr. Aqsa Akram: Conceptualization, Methodology, Data Curation, Formal Analysis, Writing Original Draft Preparation, Writing Review and Editing.

Ethical Statement

This was a retrospective cohort study utilizing de-identified electronic health record (EHR) data, with the ground truth confirmed by post-operative histopathology. The study protocol was reviewed and approved by the Institutional Review Board (IRB) of Fatima Memorial Hospital, Lahore, Pakistan, prior to data access.

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Conflict of Interest Disclosure

The author declares **no conflicts of interest** regarding the publication of this article.

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