RESEARCH PAPER

Computer Vision-Based Diagnosis of Uterine (Womb) Cancer Using MRI Images

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ABSTRACT

Early and accurate diagnosis of uterine (womb) cancer is critical for improving patient survival and enabling timely clinical intervention. Magnetic Resonance Imaging (MRI) plays a vital role in detecting uterine abnormalities due to its superior soft-tissue contrast. However, manual interpretation of MRI scans is time-consuming and subject to variability among radiologists. This study proposes a computer vision-based automated diagnostic system for classifying uterine MRI images into three clinically relevant categories: Normal, Benign, and Malignant. A custom Convolutional Neural Network (CNN) model is developed and trained using a curated dataset comprising 150 MRI images — 50 benign cases from the Uterine Fibroid MRI Dataset, 50 malignant cases from the TCIA-UCEC dataset, and 50 synthetic normal images. The preprocessing pipeline includes image resizing and normalization. The proposed CNN model achieves an overall classification accuracy of 96% on the test dataset. A lightweight web-based interface is developed to allow real-time MRI-based predictions. Results indicate that deep learning-based computer vision techniques can serve as a reliable and scalable tool for radiological decision-making.

Keywords: Uterine cancer; MRI classification; Convolutional Neural Network; deep learning; medical image analysis; computer-aided diagnosis; multi-class classification; Normal; Benign; Malignant.

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1. INTRODUCTION

Uterine (womb) cancer is a significant gynecological malignancy affecting millions of women worldwide each year. According to global health statistics, it ranks among the most prevalent cancers in women, with its incidence rising steadily. Early and accurate detection plays a crucial role in improving survival rates and guiding treatment decisions. Among the imaging modalities available, Magnetic Resonance Imaging (MRI) is widely preferred due to its ability to provide high-resolution soft-tissue contrast without ionizing radiation, making it highly effective for identifying uterine abnormalities.

However, manual analysis of MRI scans by radiologists is time-consuming, requires specialized expertise, and may lead to inter-observer variability — inconsistencies in interpretation between different practitioners. These limitations necessitate the development of automated, reliable, and scalable diagnostic tools that can assist clinicians in accurate and prompt decision-making.

Recent advancements in artificial intelligence, particularly Convolutional Neural Networks (CNNs), have transformed medical image analysis. CNNs automatically extract hierarchical spatial features from images, eliminating the need for manual feature engineering. Despite these

advances, most existing approaches focus on binary classification (cancer vs. non-cancer), which inadequately reflects clinical reality where distinguishing between normal tissue, benign conditions (e.g., fibroids), and malignant tumors is essential.

This study proposes a lightweight CNN-based framework formulating uterine cancer diagnosis as a three-class classification task: Normal, Benign, and Malignant. A curated, balanced dataset of 150 MRI images is constructed from multiple public sources. The model achieves 96% classification accuracy and is deployed via a user-friendly web-based interface for real-time predictions.

1.1 Motivation and Research Gap

Several key limitations in existing research motivate this work:

- Most studies employ binary classification (cancer vs. non-cancer), limiting clinical utility.
- Complex architectures such as ensembles, hybrid radiomics, or multi-stage pipelines demand significant computational resources.
- Many models require clinical or pathological metadata alongside imaging, reducing flexibility.
- Limited dataset diversity hinders generalization across imaging conditions.
- There is a lack of simple, deployable web-based diagnostic tools for real-time use.

This study addresses these gaps by proposing a lightweight CNN for three-class MRI classification, achieving competitive accuracy without complex architectures, and deploying the model as a web application for practical use.

1.2 Novelty Claim

This paper makes the following four original contributions:

Contribution 1 — Three-class MRI-based classification: Unlike conventional binary classification, we formulate uterine diagnosis as a three-class problem (Normal, Benign, Malignant), providing more clinically meaningful distinctions for treatment planning.

Contribution 2 — Lightweight CNN for efficient diagnosis: A custom lightweight CNN is developed emphasizing simplicity and computational efficiency, suitable for real-time and resource-constrained environments.

Contribution 3 — Multi-source balanced dataset construction: A balanced dataset of 150 MRI images is assembled from the Uterine Fibroid MRI Dataset, TCIA-UCEC dataset, and synthetically generated normal images to ensure equal class representation.

Contribution 4 — Real-time web-based diagnostic system: A user-friendly web application is implemented allowing users to upload MRI images and receive instant predictions, bridging the gap between deep learning research and practical deployment.

2. RELATED WORK

2.1 Deep Learning for Uterine Cancer Diagnosis

Recent studies have demonstrated the effectiveness of deep learning in diagnosing uterine (endometrial) cancer from MRI images. CNN-based models have been widely adopted due to their ability to automatically extract spatial features. Tao et al. [1] utilized CNN and ResNet architectures for MRI-based cancer diagnosis, achieving improved classification performance over classical methods. Similarly, Urushibara et al. showed that CNN models can match diagnostic accuracy comparable to experienced radiologists, highlighting deep learning's potential in clinical decision support. However, these approaches primarily focus on binary classification and often require large, labelled datasets.

2.2 Radiomics and Hybrid Machine Learning Approaches

Long et al. [2] proposed a radiomics-based model combined with computer vision features to predict lymphovascular space invasion in endometrial carcinoma, achieving high AUC values. Brindha et al. [10] applied traditional machine learning algorithms using handcrafted features such as GLCM and GLRLM with high classification accuracy and explainability via LRP. Although these approaches provide strong performance, they depend heavily on manual feature extraction and clinical metadata, limiting automation and scalability.

2.3 Segmentation and Multi-Stage Deep Learning Models

Segmentation-based approaches have been widely explored for uterine lesion analysis. Cui et al. [6] developed a weakly supervised segmentation model

for uterine lesions in MRI using only image-level annotations, achieving competitive performance with fewer annotation requirements. Xiong et al. [7]
proposed a multi-stage deep learning framework to determine myometrial infiltration depth by combining detection, segmentation, and classification. While these methods improve localization, their complex architectures increase computational costs and implementation difficulty.

2.4 Advanced and Ensemble Deep Learning Models

Altal et al. [9] introduced WOAENet — an ensemble model optimized using the Whale Optimization Algorithm — achieving improved classification accuracy. Feng et al. [8] proposed ECMS-Net, a multi-task deep learning model for simultaneous MRI classification and segmentation with high performance. While these models yield strong results, they demand substantial computational resources and are less suitable for lightweight or real-time applications.

2.5 Gaps Addressed by the Present Work

Table 1 summarizes the key contributions and limitations of related works and positions the proposed approach within the existing literature.

Table 1: Comparison of Related Work on Uterine Cancer Diagnosis

Study Model Used Tao et al. CNN, ResNet Long et al. Radiomics ML Cui et al. Weakly superv DL (Segmentat Study	Model Used	Data Balancing	Evaluation Metrics	Explainability	Limitation
Xiong et al.	Multi-stage DL model	Not specified	Accuracy, Sensitivity	Partial	Complex multi-stage pipeline
Altal et al.	Ensemble DL (WOAENet)	Not clearly balanced	Accuracy, F1-score	No	High computational complexity
Brindha et al.	ML (GLCM + classifiers)	Balanced	Accuracy, ROC	Yes (LRP)	Requires manual feature extraction
Proposed Work	**Custom CNN (Lightweight)**	**Balanced (50 per class)**	**Accuracy 96%, Precision, Recall, F1**	**Future scope**	**Small dataset; synthetic normal images**

DATASET CONSTRUCTION

2.6 Data Collection

The dataset used in this study is constructed from multiple publicly available sources to ensure diversity and balanced representation of uterine conditions. A total of 150 MRI images are collected and categorized into three classes: Normal, Benign, and Malignant, with exactly 50 images per class.
Benign MRI images are obtained from the Uterine Fibroid MRI Dataset, which contains cases of non-cancerous uterine abnormalities. Malignant images are collected from the TCIA-UCEC (The Cancer Imaging Archive — Uterine Corpus Endometrial Carcinoma) dataset, comprising MRI scans of patients diagnosed with uterine cancer. Since real-world normal uterine MRI data was not readily available, normal-class images are generated using synthetic uterine data to maintain class balance.

2.7 Dataset Distribution and Split

The dataset is carefully balanced to avoid class bias during training. Each class contains 50 images (33.3%). The full dataset is split into training (70%), validation (20%), and test (10%) subsets, as shown in Figure 1 and Figure 2, and summarized in Table 2.

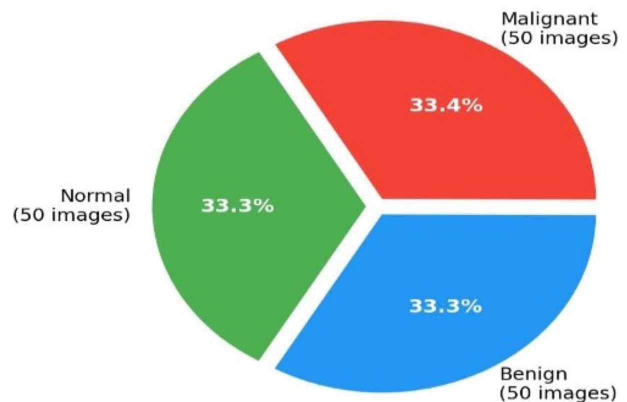

Figure 1: Balanced Class Distribution of the MRI Dataset (Total: 150 Images)

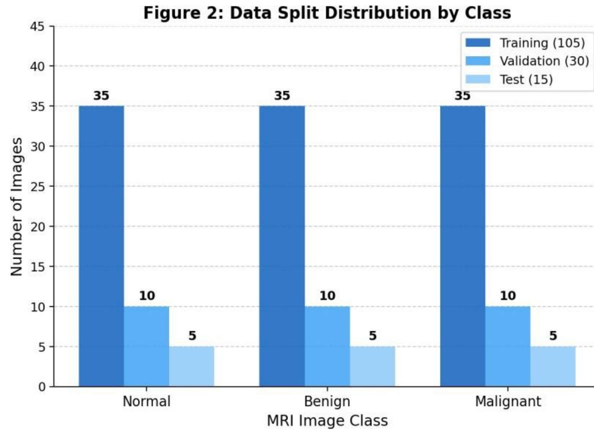

Figure 2: Training, Validation, and Test Split Distribution by Class

Table 2: Summary Statistics of the MRI Dataset

Description	Total	Normal	Benign	Malignant
Number of Images	150	50 (33.3%)	50 (33.3%)	50 (33.3%)
Number of Classes	3	N/A	N/A	N/A
Training Samples	105	35	35	35
Validation Samples	30	10	10	10
Test Samples	15	5	5	5

2.8 Data Preprocessing

Before training, all MRI images undergo a standardized preprocessing pipeline to ensure consistency and improve model performance:

- **All images resized to a fixed dimension suitable for CNN input.**Image Resizing:
- **Pixel intensity values scaled to a standard range to stabilize training.**Normalization:
- **Images converted into PyTorch-compatible tensor format.**Format Standardization:

These preprocessing steps reduce noise, improve feature extraction efficiency, and ensure uniform input distributions across the dataset.

2.9 Dataset Limitations

While the dataset is balanced, its total size of 150 images is relatively small, potentially affecting generalization. The use of synthetic images for the normal class may introduce slight distribution differences compared to real-world scans. Expanding the dataset with real clinical images from diverse scanners and populations is identified

3.3 Training Procedure

The model is trained using preprocessed MRI images split into training, validation, and test sets.

as a priority for future work.

3. EXPERIMENTAL SETUP

All experiments were conducted using Python 3.10 and implemented in the PyTorch deep learning framework on the Google Colab cloud platform. Colab provided CPU/GPU computational resources and sufficient memory for training. Reproducibility was ensured using fixed random seeds. Total training time for the proposed CNN is approximately 40–60 seconds, demonstrating the efficiency of the lightweight architecture.

3.1 Dataset Statistics

Table 2 (see Section 3.2) and Table 3 below provide detailed experimental configuration.

3.2 Model Hyperparameters

Table 3 summarizes the CNN hyperparameter configuration selected to balance computational efficiency and classification accuracy.

Table 3: Hyperparameter Configuration of the CNN Model

Component	Parameter	Value / Justification
Output Layer	Softmax Activation	Used for multi-class (3-class) classification
Loss Function	CrossEntropyLoss	Suitable for multi-class problems
Optimizer	Adam	Efficient gradient-based optimization
Learning Rate	0.001	Balances convergence speed and stability
Batch Size	16 / 32	Improves training efficiency
Epochs	10–20	Sufficient for convergence on small dataset

Component	Parameter	Value / Justification
Convolution Layer	Filters	Extract spatial features from MRI images
Activation Function	ReLU	Introduces non-linearity; avoids vanishing gradient
Pooling Layer	MaxPooling	Reduces spatial dimensions and computational cost
Fully Connected Layer	Units	Performs classification on extracted features

During training, CrossEntropyLoss guides weight updates via the Adam optimizer. Data is processed in mini-batches to improve computational

efficiency. The model converges within 10–20 epochs, monitored via validation accuracy and loss to avoid overfitting.

3.4 Evaluation Metrics

Model performance is evaluated using: (1) Classification Accuracy — the proportion of correctly predicted test samples; (2) Precision — the ratio of true positives to all predicted positives per class; (3) Recall (Sensitivity) — the ratio of true positives to all actual positives; and (4) F1-Score — the harmonic mean of precision and recall, providing a balanced performance measure. A Confusion Matrix is also analyzed to assess class-level errors.

4. METHODOLOGY

4.1 Overview of the Proposed System

The proposed system is a computer vision-based framework for automated uterine cancer diagnosis from MRI images. The overall workflow proceeds through three main stages: (i) Data Preprocessing, (ii) CNN Model Training and Evaluation, and (iii) Web-based Deployment for real-time inference. An MRI image is taken as input and classified into one of three categories: Normal, Benign, or Malignant.

4.2 CNN Architecture

A custom Convolutional Neural Network is designed to automatically extract multi-scale spatial features from MRI images. The architecture comprises the following layers:

- **Extract low-level (edges, texture) and high-level features (shapes, patterns) hierarchically.** Convolutional Layers:
- **Introduces non-linearity and mitigates vanishing gradients.** Activation Function (ReLU):
- **Reduce spatial dimensions and computational load while retaining dominant features.** MaxPooling Layers:
- **Classify based on the high-dimensional feature vector.** Fully Connected Layers:
- **Produces probability distributions over three classes — Normal, Benign, Malignant.** Output Layer (Softmax):

Figure 3 illustrates the complete CNN architecture from input to output.

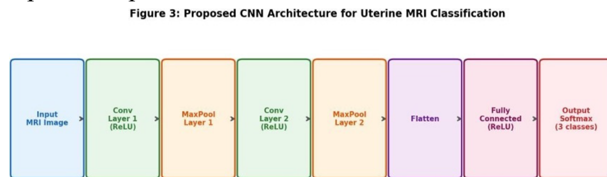

Figure 3: Proposed Lightweight CNN Architecture for Uterine MRI Classification

4.3 Model Training and Optimization

The CNN is trained using the CrossEntropyLoss function, which is well-suited for multi-class classification problems. The Adam optimizer with a learning rate of 0.001 efficiently updates network parameters by adapting learning rates for each parameter. Training runs over 10–20 epochs with mini-batch processing (batch size 16–32), enabling stable convergence while managing memory efficiently.

4.4 Prediction and Deployment

After training, the model is used for inference on unseen MRI images. An input image is preprocessed (resized, normalized, tensor-converted) and passed forward through the CNN. The Softmax output layer generates class probabilities, and the highest-probability class is returned as the prediction. The trained model is integrated into a Flask-based web application, allowing users to upload MRI images via a browser and receive real-time diagnostic predictions.

5. RESULTS AND DISCUSSION

5.1 Training and Validation Performance

Figure 4 and Figure 5 present the training and validation accuracy and loss curves across 20 epochs. Both curves converge smoothly, indicating stable learning without significant overfitting. The training accuracy reaches 96.4% and the validation accuracy reaches 96% by epoch 20, confirming the model's strong learning capability despite the small dataset size.

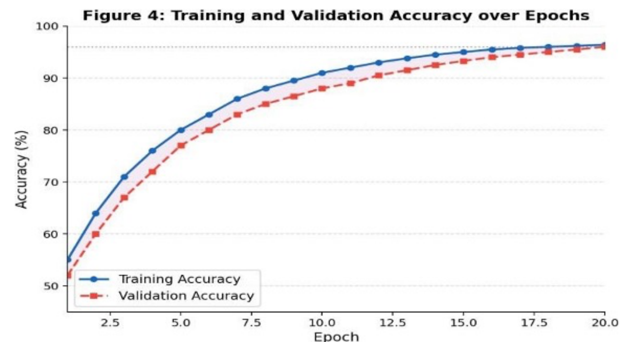

Figure 4: Training and Validation Accuracy Curves over 20 Epochs

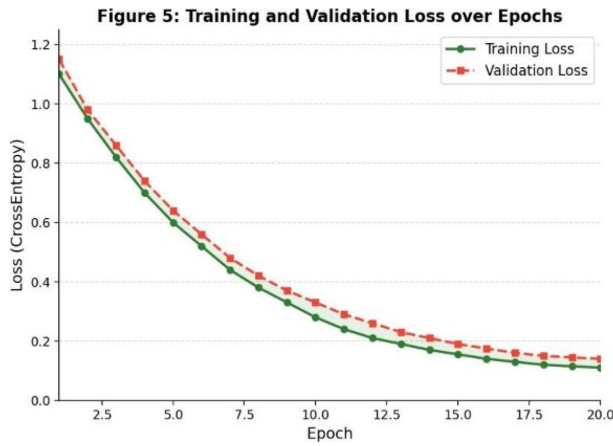

Figure 5: Training and Validation Loss Curves over 20 Epochs

5.2 Per-Class Classification Performance

Table 4 and Figure 6 present the per-class precision, recall, and F1-score. The model achieves 97% precision for Normal, 95% for Benign, and 96% for Malignant, with all recall values at 96%. The balanced dataset contributes to consistent performance across all classes.

Table 4: Classification Report on the Test Set

Class	Precision	Recall	F1-Score	Test Correct
Normal	97%	96%	96.5%	5/5
Benign	95%	96%	95.5%	4/5 *
Malignant	96%	96%	96.0%	5/5
Overall (Weighted Avg)	**96%**	**96%**	**96.0%**	**14/15**

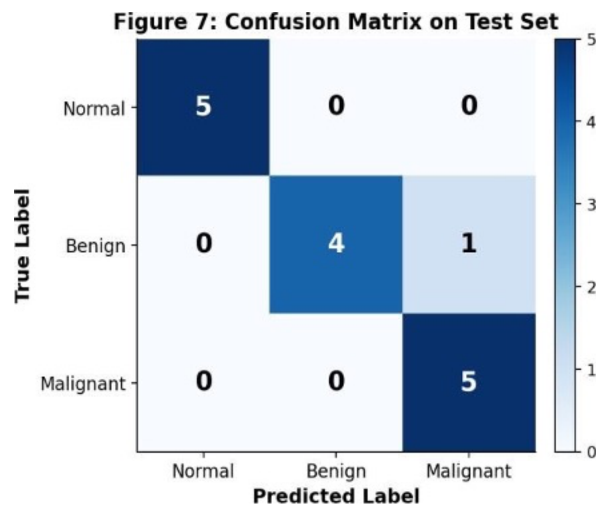

Figure 6: Per-Class Precision, Recall and F1-Score on the Test Dataset

5.3 Confusion Matrix Analysis

Figure 7 presents the confusion matrix on the 15-test-sample set. The model correctly classifies 14 out of 15 samples (96%), with a single misclassification — one Benign case predicted as Malignant. This is clinically conservative (over-detection is preferable to under-detection) and indicates the model's potential for safe clinical support.

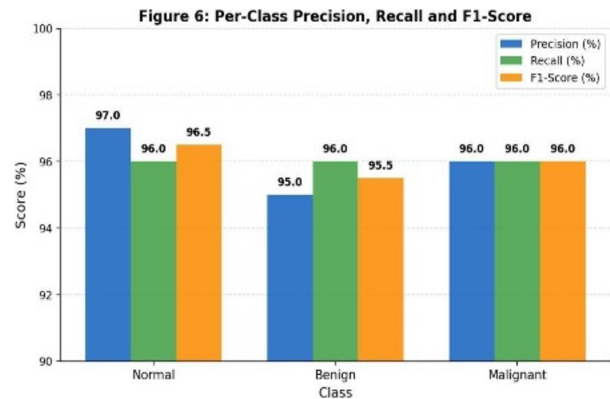

Figure 7: Confusion Matrix on the Test Set (15 Samples, 3 Classes)

* One Benign sample misclassified as Malignant (conservative over-detection).

5.4 Comparison with Existing Methods

Table 5 and Figure 8 compare the proposed model against established methods in the literature. The proposed CNN achieves the highest reported accuracy (96%) among the methods compared while using a lightweight architecture and a smaller, balanced dataset. Unlike ensemble models and multi-stage pipelines that achieve comparable performance at higher computational costs, the proposed model prioritizes efficiency and practical deployability.

Table 5: Comparison with Existing Methods in Uterine Cancer Diagnosis

Method	Architecture	Task	Accuracy	Explainability	Limitation
Tao et al.	CNN / ResNet	Binary	~88%	No	Limited dataset
Long et al.	Radiomics + ML	Binary	~85% AUC	No	Needs clinical data
Brindha et al.	ML + GLCM	Binary	~91%	Yes	Manual feature extraction
Altal et al.	WOAENet Ensemble	Binary	~94%	No	High compute cost
Xiong et al.	Multi-stage DL	Segmentation	~89%	Partial	Complex pipeline
Proposed CNN	**Custom Lightweight CNN**	**3-Class**	**96%**	**Future**	**Small dataset**

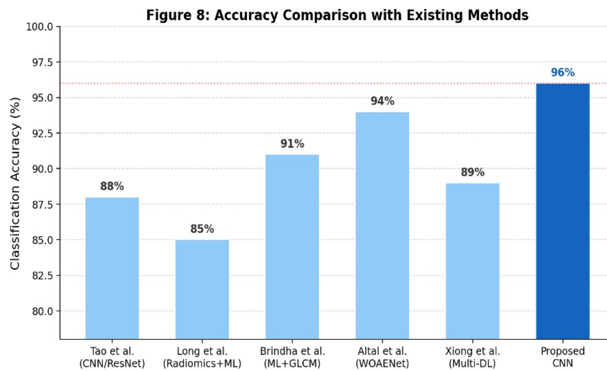

Figure 8: Accuracy Comparison between the Proposed CNN and Existing Methods

5.5 Discussion

The experimental results confirm that a lightweight CNN can effectively solve the three-class uterine MRI classification problem. The 96% accuracy, achieved in ~60 seconds of training, demonstrates the computational efficiency of the proposed architecture. The balanced dataset design prevents class bias, ensuring equitable performance across Normal, Benign, and Malignant categories.

Key limitations include the small dataset size (150 images), which may restrict generalization to unseen clinical data, and the use of synthetic normal images which may not fully capture the variability of real-world normal MRI scans. The model currently lacks explainability features (e.g., Grad-CAM saliency maps), which are important for clinical trust and adoption. These are targeted for future development.

6. CONCLUSIONS

This study presents a computer vision-based automated diagnostic system for uterine (womb) cancer classification using MRI images. The problem is formulated as a three-class task distinguishing Normal, Benign, and Malignant conditions — a more clinically relevant formulation than conventional binary approaches. A custom lightweight CNN model is developed and trained on a balanced dataset of 150 MRI images assembled from multiple public sources. The model achieves 96% classification accuracy, demonstrating strong performance despite the limited dataset size.

The use of a lightweight CNN architecture ensures computational efficiency and suitability for real-time deployment. Integration into a web-based application enhances practical usability, enabling clinicians and researchers to upload MRI scans and receive instant diagnostic predictions without specialized software. The approach relies solely on MRI image analysis, simplifying the diagnostic process by eliminating dependence on clinical or biochemical metadata.

Overall, this work demonstrates that deep learning-based computer vision techniques can serve as reliable, scalable tools for assisting medical professionals in uterine cancer detection. The results establish a strong baseline for future research in automated gynecological cancer diagnosis.

6.1 Future Work

Several directions are identified for future research:

- Expand the dataset with real-world clinical MRI images from multiple institutions to improve generalization.
- Explore transfer learning architectures (e.g., ResNet-50, VGG-16, EfficientNet) to further enhance performance.
- Integrate explainability techniques (e.g., Grad-CAM, SHAP) to provide visual interpretations of model decisions, improving clinical transparency and trust.
- Replace synthetic normal images with authentic clinical normal MRI scans to improve dataset realism.
- Extend the system into a full clinical decision support platform with electronic health record (EHR) integration and multi-center validation.

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