Multimodal Atrial Fibrillation Risk Stratification: Fusing Post-Stroke Brain DWI and Clinical Data

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***Abstract*—Atrial fibrillation (AF) is a significant risk factor for ischemic stroke recurrence, yet its diagnosis remains challenging through short-term heart monitoring due to its often paroxysmal and silent nature. Despite its diagnostic superiority, prolonged cardiac monitoring is typically impractical and not cost-effective for widespread implementation. We propose a novel AF risk stratification framework using a multimodal deep learning approach that integrates diffusion-weighted imaging (DWI) of the brain with clinical patient data. Our methodology combines convolutional neural networks (CNNs) for image analysis and gradient-boosted decision trees (GBDT) for clinical data, leveraging an innovative fusion strategy and an auxiliary loss function based on infarct location. The proposed approach achieves an area under the receiver operating characteristic (AUROC) of 89.18%, outperforming unimodal counterparts. This work contributes to the field by enabling AF risk stratification from brain DWI, utilizing weak supervision, and introducing a novel early and late-stage data fusion approach. Our method easily integrates with existing workflows and can identify high-risk individuals requiring intensive cardiac monitoring.**

***Index Terms*—Atrial fibrillation (AF), ischemic stroke, diffusion-weighted imaging (DWI), decision trees, and multimodal deep learning.**

I. Introduction

Atrial Fibrillation (AF) is a common and significant risk factor for ischemic stroke [1], [2]. Detecting AF is critical for secondary stroke prevention. Yet, it remains a challenge due to the intermittent and silent nature of many AF episodes and the limitations of traditional monitoring methods that heavily rely on monitoring length. Moreover, these methods are often costly or invasive. In clinical practice, the timely and accurate identification of AF can be difficult, leading to potential delays in treatment and increased risk of recurrent strokes. Due to the impracticality of prolonged heart monitoring for all stroke patients, a comprehensive AF risk stratification framework is crucial to identify individuals who would benefit from long-term cardiac monitoring [3]. Such a framework would not only optimize resource allocation but also enable targeted preventive strategies for high-risk patients.

Brain magnetic resonance imaging (MRI), and mainly, diffusion-weighted imaging (DWI) offer superior resolution and sensitivity for detecting early ischemic changes, allowing for more precise identification of infarct regions [4], [5] compared to computed tomography (CT) scans. DWI is particularly valuable as it corroborates clinical diagnoses and uncovers ischemic patterns that provide insights into the stroke's underlying cause [6]–[10]. While MRI-DWI imaging provides crucial insights into stroke etiology, the specific ischemic patterns indicative of atrial fibrillation remain incompletely characterized. Consequently, it remains challenging for clinicians to identify AF solely from imaging scans.

While deep learning (DL) models have shown potential in identifying AF from brain MRI, research in this application remains limited [11], [12]. Further, relying solely on imaging analysis potentially overlooks crucial patient-specific risk factors and limits interpretability, which is essential in clinical decision-making. Therefore, fusing clinical patient data with imaging analysis enhances AF risk stratification by providing a more comprehensive context, improving interpretability, and potentially enabling identification of patient subgroups. This multimodal approach not only increases accuracy [13], [14] but also allows for more personalized and nuanced stroke management strategies, considering both imaging findings and individual clinical risk factors.

We propose a novel multimodal approach for AF risk stratification in post-stroke patients by fusing brain DWI and clinical data. Our model integrates a convolutional neural network (CNN) for image processing with a gradient boosted decision tree (GBDT) for clinical data analysis, leveraging the strengths of both architectures. The CNN model processes brain DWI images and produces a logit, which is used in two ways: 1) to generate an image-based AF likelihood probability via softmax, and 2) as an input feature for the GBDT, combined with clinical data. Finally, the class probabilities from the CNN and GBDT models are averaged, effectively ensembling the two approaches to produce the final AF likelihood probabilities. The contributions of this work are:

- A novel multimodal approach for post-stroke AF risk stratification, integrating brain DWI and clinical data through CNNs and GBDTs, achieving superior performance (89.18% AUROC) over unimodal methods.
- An innovative data fusion technique featuring unique early and late-stage fusion, combining strengths of CNN and GBDT models to enhance overall predictive power.
- Introduction of an auxiliary loss function based on infarct location, eliminating the need for time-consuming

segmentation masks and improving efficiency.
- Enhanced clinical interpretability through SHapley Additive exPlanations (SHAP) analysis, providing insights into feature interactions and their roles in AF prediction, thus aiding in transparent and explainable clinical decision-making.
- Improved clinical workflow integration, identifying high-risk individuals for intensive cardiac monitoring while leveraging GBDT's feature importance for actionable insights.

II. Related Works

A. AF Identification

Despite the vast amount of research conducted in deep learning applications in stroke imaging, only two concurrent works that align with our approach for AF identification from stroke imaging are published in the literature. Zhang *et al*. [11] combine extracted features using a CNN model with radiomic features to identify AF from brain MRI, achieving an AUROC of 79.9%. Their approach relies on costly, time-consuming segmentation masks for radiomic features and excludes clinical data crucial for stroke and AF management. The lack of detailed discussion on methodology, dataset, and results hinders a thorough assessment of its contributions.

Similarly, Kuo *et al*. [12] build a small dataset of 29 patients to differentiate between cancer-associated thrombosis (CAT) and AF-related strokes, subgroups of embolic strokes. They achieve an AUROC of 74.44% and 82.5% when using DWI images only or DWI images combined with clinical data, respectively. Fundamental limitations include a small dataset, the rarity of CAT-related strokes compared to AF-related ones, and excluding non-embolic stroke etiologies. These factors may introduce bias in the results.

Although both studies demonstrate the potential of using brain MRI in AF identification, the limitations necessitate further research to develop an efficient multimodal classification framework to detect the underlying AF by integrating clinical data and brain MRI. Additionally, acquiring precise segmentation of infarct regions in clinical practice (as in [11]) is challenging and often not feasible. As a result, alternative methods for AF identification need to be developed.

B. Fusion Algorithms

Algorithmic choice is crucial in maximizing the benefits of multimodal data fusion. For example, CNNs excel in image analysis by automatically extracting and learning hierarchical features from complex imaging data. GBDTs stand out in tabular data analysis due to their more robust performance and better interpretability [15].

Neural networks and GBDTs have been employed together in unimodal tasks, with one handling feature extraction while the other predicting the outcome [16]–[21]. Some studies have also explored joint training of GBDTs and neural networks [22]. Most existing works fuse data at the decision level, combining predictions from GBDTs and other models for different modalities rather than integrating the features. Consequently, this may lead to the loss of potential insights derived from the interaction between different modalities. On the other hand, Xu *et al*. [23] used CNNs to extract features and fed these into GBDT and a classification head, generating two independent class probabilities that are later averaged. Although promising, to our knowledge, this strategy has not yet been applied to multimodal data fusion.

TABLE I
Dataset demographics and baseline variables in atrial fibrillation (AF) and large-artery atherosclerosis (LAA) groups, including vascular risk factors and stroke location.

Parameter	**AF** (137)	**LAA** (93)
Age (SD)	75.5 (11.3)	64.5 (15.3)
Female sex	52 (37.9%)	28 (30.1%)
Hypertension	85 (62%)	57 (61.2%)
Ischemic heart disease	24 (17.5%)	12 (12.9%)
Congestive heart failure	11 (8%)	1 (1%)
Previous stroke	18 (13.1%)	17 (18.2%)
Previous transient ischemic attack (TIA)	15 (10.9%)	5 (5.3%)
Diabetes	32 (23.3%)	31 (33.3%)
Stroke location		
Left	58 (42.3%)	42 (45.1%)
Right	52 (37.9%)	29 (31.1%)
Bilateral	5 (3.6%)	6 (6.4%)
Posterior circulation	22 (16%)	16 (17.2%)

III. Methodology

A. Data Collection

A retrospective dataset of 230 post-stroke patients was collected to develop a multimodal AF identification framework. The ethics approval was obtained from the Royal Melbourne Hospital Ethics Committee (QA 2013.072). For each patient, a DWI image acquired during the acute phase of the stroke, along with demographics and clinical history, was utilized for model development. Table I provides the details and patient history.

DWI images were obtained using five scanners (Siemens Aera, Siemens Prisma Fit, Siemens Skyra, Siemens Magnetom Essenza, and Philips Ingenia) because some patients were transferred from other hospitals. The imaging parameters used in this study included magnetic field strengths of 1.5 or 3 Tesla, repetition time ranging from 4100 to 7920 ms, echo time from 55 to 104 ms, flip angles of 0 or 180 degrees, b-values of 0 or 1,000 $\mathrm{sec}/\mathrm{mm}^2$, slice thicknesses of 0.256 to 7.474 mm, slice spacing of 2 to 7.5 mm, and pixel spacing of 0.548 to 2 mm.

The dataset was annotated using the causative classification of stroke (CCS) system [24], focusing on AF as the target class and large-artery atherosclerosis (LAA) as the control group, while excluding all other stroke etiologies. We chose the Causative Classification of Stroke (CCS) system [24] for dataset annotation due to its superior accuracy in categorizing stroke etiologies compared to Trial of Org 10172 in Acute Stroke Treatment (TOAST) [25] and Atherosclerosis, Small-vessel disease, Cardiac source, and Other cause (ASCO) [26] systems. Our study focused on LAA and AF subtypes,

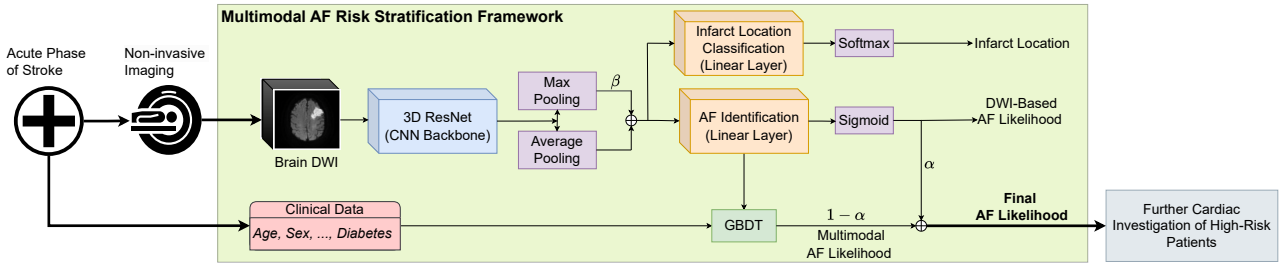

Fig. 1. Overview of our multimodal (combining image and clinical data) model for AF risk stratification. A CNN processes brain DWI images, extracting features for multiple purposes: generating image-based class probabilities, feeding into a GBDT model alongside clinical data, and predicting infarct location (left, right, bilateral, or posterior circulation) for auxiliary loss calculation. The final AF likelihood (AF vs. non-AF) is determined by weighted averaging (using α) the CNN and GBDT outputs. β is a weight used to combine average pooling and max pooling, and is set to 0.5. (CNN: convolutional neural network, DWI: diffusion-weighted imaging, GBDT: gradient boosting decision tree, AF: atrial fibrillation)

excluding others, due to their higher recurrence rates, severity, and the significant impact of early intervention. Although limited, our focus represents the first attempt to develop a fully automated risk stratification framework for AF from brain MRI scans. Starting with LAA and AF allowed us to establish a robust foundation with reliable ground truth data, setting the stage for future expansion to include other stroke subtypes and enhance the model's clinical applicability.

B. Data Preprocessing

All DWI images were resampled to [8mm, 1.5mm, 1.5mm] using nearest neighbor interpolation to maintain voxel consistency. Further, the images were resized to a shape of (32, 256, 256), ensuring uniform input dimensions for the CNN model and their intensity values were normalized using Z-transform. During training, we applied elastic deformations, random flips in all three planes, random 90-degree rotations, Gaussian noise addition, random scaling, and cropping to enhance the model's generalization capability. For the clinical data, the numerical feature, *i.e.* the 'Age' was scaled using Z-transform, and categorical variables were converted into binary representations. Furthermore, missing values were imputed using the mode of the corresponding column.

C. Multimodal AF Identification Network

Our novel multimodal approach for AF risk stratification in post-stroke patients integrates brain DWI with clinical data, using CNNs for image analysis and GBDTs for clinical data processing (shown in Fig. 1). The CNN backbone processes DWI images, producing a logit to generate image-based class probability, feed into the GBDT model, and predict infarct location for auxiliary loss calculation. We use pre-trained 3D ResNet models from medical image segmentation networks [27]. The CNN output logit is concatenated with clinical data and fed into a GBDT model, which produces its class probability. Then, the final class probability, $\hat{y}$, is obtained by weighted averaging (α) the outputs from both models using:

$$\hat{y} = \alpha * \text{out}_{\text{CNN}} + (1 - \alpha) * \text{out}_{\text{GBDT}}. \quad (1)$$

D. Loss Function

We incorporate a weak, image-level integer label indicating infarct location to guide the CNN's focus without detailed annotations. This label specifies stroke hemisphere involvement (left, right, bilateral, or posterior circulation). Using a cross-entropy loss function, we use this label to introduce an auxiliary infarct location-based loss, L_{ILL}. Using cross-entropy loss function. The AF identification loss, L_{AF}, is also calculated using the binary cross entropy loss function. The auxiliary loss is multiplied by hyperparameter λ and added to the AF loss to calculate the total loss function used for updating the model's weights, as shown below:

$$L_T = L_{AF} + \lambda L_{ILL}. \quad (2)$$

IV. Experiments and Results

We perform extensive experiments to assess the effectiveness of our proposed method. Standard binary classification metrics are used to evaluate the performance of the AF identification framework. Notably, AUROC evaluates the model's performance independently of the classification threshold. Since probability estimates are more relevant than class labels in our AF risk stratification approach, AUROC performs as the key metric.

A. Implementation Details

The dataset was split (using stratified sampling) into five folds (20% each), where one fold was used for testing while the others were used for training. Within each training set, a further division was made into a training (90%) and validation (10%) set for hyperparameter tuning, allowing for evaluation of model performance on unseen data while optimizing parameters and performing early stopping based on a validation subset. The experiments were repeated five times, each using a different fold for testing. Finally, the five experiments' results were aggregated and reported as mean $\pm$ standard deviation.

Adam optimizer was used with an initial learning rate of 0.0001, a weight decay of 0.01, a step scheduler for the learning rate with a step size of 20, and a decay rate of 0.8. The batch size was set to 16, and the models were trained for

TABLE II
PERFORMANCE COMPARISON: OUR METHODOLOGY OUTPERFORMS EXISTING DWI-BASED AND MULTIMODAL FRAMEWORKS IN THE LITERATURE.

Method	Modality	Accuracy	Precision	Recall	F1 score	AUROC
Zhang *et al*. [11]	DWI	70	63.8	92.5	75.5	79.9
Kuo *et al*. [12]	DWI	78.57	-	60	-	74.44
Kuo *et al*. [12]	DWI and Clinical	85.71	-	75	-	82.50
Proposed	DWI and Clinical	76.08 ± 4.55	$\mathbf{77.58 \pm 8.20}$	88.18 ± 12.65	$\mathbf{81.27 \pm 3.33}$	$\mathbf{89.18 \pm 5.57}$

TABLE III
PERFORMANCE COMPARISON OF MODELS, INCLUDING UNIMODAL RESNET34 AND GBDT, IMPACT OF AUXILIARY LOSS ($\lambda = 0.1$), MULTIMODAL FUSION (DWI+CLINICAL) AND WEIGHTED AVERAGING ($\alpha = 0.7$). THE PROPOSED MULTIMODAL (WITH RESNET34 + GBDT) MODEL PERFORMS BEST.

Method	Accuracy	Precision	Recall	F1 score	AUROC
Unimodal (clinical data) with GBDT	59.56 ± 3.53	66.56 ± 3.81	66.28 ± 7.79	65.92 ± 2.94	64.61 ± 7.51
Unimodal (DWI) with ResNet34	75.65 ± 5.73	$\mathbf{83.56 \pm 7.64}$	76.53 ± 13.67	78.52 ± 5.68	82.84 ± 8.17
Unimodal (DWI) with ResNet34 & $0.1 * L_{ILL}$	71.73 ± 7.14	75.26 ± 10.77	82.78 ± 15.93	77.32 ± 7.23	84.71 ± 8.32
Multimodal with GBDT	$\mathbf{78.69 \pm 4.43}$	$\mathbf{83.66 \pm 6.43}$	81.71 ± 10.90	$\mathbf{81.87 \pm 4.17}$	87.62 ± 2.85
Multimodal with ResNet34 & GBDT (**proposed**)	76.08 ± 4.55	77.58 ± 8.20	$\mathbf{88.18 \pm 12.65}$	$\mathbf{81.27 \pm 3.33}$	$\mathbf{89.18 \pm 5.57}$

250 epochs, with early stopping applied based on validation loss to prevent overfitting. To implement GBDT out of the box, we utilized the XGBoost library [28] with its default settings.

B. Comparison with Previous Works

In our best model, ResNet34 is the CNN backbone, λ is set to 0.1, and α is set to 0.7. We compare the results achieved by this model with the existing works in the literature. The datasets employed in these studies differ from the one utilized in our research in several key aspects, such as the size, the diversity of the data, and the specific features included. Zhang *et al*. [11] did not provide sufficient methodological details, which precludes the replication of their approach on our dataset. Additionally, the method proposed by Kuo *et al*. [12] exhibited suboptimal performance on our dataset. Their published results are included to provide the context.

Table II demonstrates the efficacy and effectiveness of the proposed method. Our unimodal and multimodal models significantly outperform their counterparts in the literature. It should also be noted that segmentation masks were not used in this work, unlike Zhang *et al*. [11]. Moreover, the size of our dataset is significantly larger than Kuo *et al*. [12] dataset, and the control group in our study is LAA strokes as opposed to CAT-related strokes, making our study more meaningful regarding the clinical applicability.

C. Ablation Studies

Our comprehensive evaluation of the proposed approach included experiments with unimodal image (DWI) and clinical data-based models (ResNet34 and GBDTs, respectively), an auxiliary loss function ($\lambda = 0.1$), multimodal data fusion (DWI+clinical) for GBDTs, and weighted averaging of ResNet34 and GBDT models ($\alpha = 0.7$). Table III shows the results.

Results showed that the GBDT model using clinical data alone performed poorly, while the ResNet34 model trained on DWI images significantly outperformed it. The auxiliary loss improved the DWI-based model's performance by 2%, and the multimodal GBDT achieved a 3% gain over the image-based model. The ensemble of unimodal ResNet34 and multimodal GBDT models yielded the best results. Further experiments with hyperparameters revealed that small weights for the auxiliary loss improved performance by focusing on infarct regions, with optimal results at $\lambda = 0.1$. Most models performed best for model ensembling with $\alpha = 0.5$, except ResNet34, which achieved optimal results at $\alpha = 0.7$.

D. Interpretability of the Proposed Method

We employed SHAP [29] to interpret the importance of GBDT's features. In the clinical-only model, we found 'Age' to be the most significant AF risk factor consistent with clinical observations (p-value < 0.01). Upon adding image features, we observed that the image features improved the model performance and became the most significant predictor, demonstrating the potential of brain DWI and fusion model for AF risk stratification.

V. CONCLUSION

Our proposed multimodal deep learning framework offers a promising solution for AF risk stratification by effectively combining brain DWI and clinical data. Integrating CNNs and GBDT with a novel fusion strategy and infarct location-based auxiliary loss function enables superior predictive performance. This approach outperforms unimodal methods and seamlessly integrates into clinical workflows, providing a practical tool for identifying high-risk individuals who will benefit from more intensive cardiac monitoring. Our approach aids in automated AF diagnosis and secondary stroke prevention.

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