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ORIGINAL ARTICLE

Fluid-attenuated inversion recovery magnetic resonance imaging-derived artificial intelligence dementia probability: A workflow-integrated decision support model for outpatient triage

Şeref Barbaros Arik[1], Murat Şimşek[2], Aslıhan Baran[3], Gökhan Şahin[4]

[1]Department of Radiology, Yüksek İhtisas University Medicalpark Hospital, Ankara, Türkiye
[2]Ostim Technical University, Artificial Intelligence Engineering, Ankara, Türkiye
[3]Department of Neurology, Yüksek İhtisas University, Medicalpark Hospital, Ankara, Türkiye
[4]Department of Emergency, Medicalpark Hospital, Ankara, Türkiye

ABSTRACT

Objectives: This study aimed to evaluate the diagnostic performance of an artificial intelligence (AI)-based decision support model that estimates the probability of dementia using only routine fluid-attenuated inversion recovery (FLAIR) magnetic resonance imaging (MRI) sequences and to assess its potential role as a triage tool in outpatient clinical settings.

Patients and methods: This retrospective single-center study included 96 patients who underwent brain MRI and had established clinical and neuropsychological diagnoses between January 2021 and December 2024. A previously published convolutional neural network model trained on 6,400 open-access MRI scans was applied to our institutional dataset to evaluate its diagnostic performance in a real-world clinical setting. For clinical interpretability, a predefined threshold of 50% was used to classify cases, and receiver operating characteristic analysis was performed to assess discriminative performance.

Results: The dementia group (n = 47) had a mean age of 71.76 ± 8.32 years (range, 55 to 90 years) and included 25 females (53.2%) and 22 males (46.8%). The control (nondementia) group (n = 49) had mean age of 75.18 ± 7.48 years (range, 55 to 89 years) and included 25 females (51.0%) and 24 males (49.0%). The AI model achieved an accuracy of 89.6%, sensitivity of 78.7%, specificity of 100%, and an AUC of 0.937. The dementia probability (%) strongly correlated with clinical diagnoses (r = 0.762, $p < 0.001$). Notably, no false-positive cases were observed in this cohort, indicating high reliability of positive classifications. McNemar and Binomial tests confirmed that the classification performance was significantly better than chance ($p < 0.001$).

Conclusion: Artificial intelligence-derived dementia probability from routine FLAIR MRI provides a rapid and standardized output that may support clinical decision-making at the initial point of care. The absence of false-positive cases is consistent with the potential utility of the model as a rule-in decision-support tool, supporting prioritization of patients for further diagnostic evaluation. These findings highlight the potential of a simple, single-sequence AI approach to enhance workflow efficiency in neuroradiology practice without replacing clinical judgment.

Keywords: Alzheimer's disease, artificial intelligence, convolutional neural network, decision support, dementia, flair; magnetic resonance imaging; triage model.

Dementia, particularly Alzheimer's disease, is an increasingly prevalent neurodegenerative condition that imposes substantial clinical and socioeconomic burdens worldwide. Early and accurate diagnosis is critical, as therapeutic efficacy and patient management are optimized when interventions are introduced at the earliest stages. Nevertheless, clinical diagnosis is often delayed due to nonspecific symptoms, and definitive confirmation typically requires histopathology

Correspondence: Şeref Barbaros Arik, MD. Yüksek İhtisas Üniversitesi Medicalpark Hastanesi, Radyoloji Anabilim Dalı, 06530 Çankaya, Ankara, Türkiye.
E-mail: serefbarbaros@yiu.edu.tr
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or postmortem evaluation. Consequently, many patients remain undiagnosed until advanced stages of disease.[1-3]

Globally, more than 55 million people are currently living with dementia, a number projected to more than double by 2050.[4,5] In Türkiye alone, an estimated 800,000 individuals are affected, with prevalence expected to rise sharply due to population aging.[6-8]

This growing burden has prompted international guidelines to recommend structural imaging, preferably magnetic resonance imaging (MRI), for patients with suspected dementia, not only to exclude secondary causes but also to identify supportive features of neurodegenerative disease. While volumetric MRI analyses and visual rating scales (e.g., global cortical atrophy, medial temporal atrophy, and Koedam scales) have diagnostic value, their systematic application is often impractical in routine outpatient settings due to workload constraints. This highlights the need for automated tools capable of providing rapid, reliable assessments.[9-13]

Unlike many prior artificial intelligence (AI) approaches that rely on multisequence MRI protocols or volumetric analyses, the present study evaluates the real-world clinical applicability of a previously published convolutional neural network (CNN) that was originally developed using T1-weighted MRI images. Rather than developing a new AI model, we investigated whether this pretrained model could provide clinically useful patient-level dementia probability (%) scores when applied to routinely acquired Fluid-attenuated inversion recovery (FLAIR) MRI sequences in an independent real-world clinical cohort. Fluid-attenuated inversion recovery sequences were selected because they are routinely acquired as part of standard brain MRI protocols, maximizing feasibility and facilitating integration into everyday clinical workflows. The primary objective was not to establish a definitive diagnosis but to explore a triage-oriented framework in which AI-derived probability scores may support early clinical decision-making and prioritization of further diagnostic evaluation.

The original study introducing this CNN acknowledged the lack of evaluation on real-world clinical data. Accordingly, the present study was designed to assess the real-world clinical applicability of the previously published model using an independent institutional cohort.

PATIENTS AND METHODS

This retrospective study included 47 patients with a clinical diagnosis of primary degenerative dementia who underwent brain MRI at the Yüksek İhtisas University, Medical Park Ankara Hospital, Neurology Outpatient Clinic, between January 2021 and December 2024. All dementia diagnoses were established by neurologists based on clinical evaluation and neuropsychological testing according to contemporary diagnostic guidelines. Axial FLAIR sequences were retrieved from the institutional Picture Archiving and Communication System (PACS). As a comparison group, we selected 49 individuals. Control subjects were selected to have no clinically significant intracranial abnormalities on MRI. Individuals with extensive white matter hyperintensities, lacunar infarcts, intracranial hemorrhage, mass lesions, or other structural abnormalities that could substantially affect FLAIR image interpretation were excluded. This approach was intended to minimize confounding FLAIR abnormalities while maintaining a control cohort representative of routine clinical practice. Written informed consent was obtained from all participants. The study protocol was approved by the Yüksek İhtisas University Health Sciences Research Ethics Committee (Date: 03.07.2024; No. 2024-03-04). The study was conducted in accordance with the principles of the Declaration of Helsinki.

All scans were acquired on a Siemens Magnetom Altea 1.5 Tesla (Siemens Healthineers, Erlangen, Germany) using axial FLAIR (repetition time, 6000 msec; echo time, 84 msec; slice thickness, 5 mm) sequences. A board-certified radiologist performed quality control and excluded studies with motion or incomplete coverage. We retrieved the images from the institutional PACS at the highest available JPEG resolution, anonymized them, and standardized them using a consistent preprocessing pipeline. During model inference, the images were automatically resized to the input dimensions (128 × 128 pixels) required by the previously published CNN architecture. Although this preprocessing step may have reduced fine anatomical detail, it was applied uniformly to all cases as part of the original inference pipeline, and visual quality control was performed to ensure consistency and preserve diagnostic integrity. To keep anatomical coverage comparable, we removed the upper two to three slices without supratentorial parenchyma and the lower two to three slices containing the cerebellum/foramen

magnum. Each subject received a study ID (1-96), and we organized approximately 15 to 20 axial FLAIR slices per patient into individual folders for downstream analysis.

We used a previously published CNN model originally developed by Çetin Taş and Şimşek.[14] The original CNN was developed using an open-access Alzheimer's disease dataset (Kaggle/OASIS-derived) consisting of 6,400 T1-weighted MRI images categorized as nondemented, very mild demented, mild demented, and moderate demented. The training dataset was entirely independent of the present institutional cohort. In the current study, the CNN architecture and model weights were not modified, retrained, or fine-tuned. Instead, the previously published pretrained model was applied to routinely acquired FLAIR MRI sequences from our institution to evaluate its real-world clinical performance as a decision-support tool in an outpatient neuroradiology setting. The technical details of the original model development were described in detail by Çetin Taş and Şimşek.[14]

We applied the model to 15 to 20 axial FLAIR slices per subject. Slice-level probabilities were aggregated (mean probability across all slices) to obtain a patient-level dementia probability score. For clinical interpretability, model outputs were further dichotomized into a binary endpoint ("dementia" *vs.* "nondementia"). A single patient-level dementia probability score was then compared with the clinical reference standard.

Statistical analysis

Statistical analyses were performed using Python version 3.11 software (Python Software Foundation, Wilmington, DE, USA) with the following libraries: pandas, scipy, statsmodels, and scikit-learn. We summarized the data with descriptive statistics. Based on distribution, numerical variables were reported as mean or median with minimum and maximum values, and categorical variables as counts and percentages. For between-group comparisons, an independent-samples t-test was applied when parametric assumptions were met, and a chi-square (χ^2) test was used to assess associations between categorical variables.

The distribution of AI-derived dementia probability scores was nonnormal. For clinical interpretability, a predefined threshold of 50% was used to categorize AI outputs into "dementia" and "nondementia," reflecting a clinically intuitive binary decision point in a triage setting. In addition, receiver operating characteristic analysis was performed to evaluate the discriminative performance of the model, and the optimal cutoff value was determined using the Youden index as a complementary analytical approach. Model performance was summarized with accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). A 95% confidence interval (CI) was calculated for all performance metrics. The relationship between AI probability scores and actual diagnoses was assessed using point-biserial correlation analysis, with Spearman correlation performed as a confirmatory analysis.

We used the McNemar test to assess whether differences between AI-predicted and actual classifications were statistically significant. A Binomial test evaluated whether diagnostic accuracy exceeded chance-level performance (50%). A p-value < 0.05 was considered statistically significant.

RESULTS

The cohort included a total of 96 subjects. The dementia group (n = 47) had a mean age of 71.76 ± 8.32 years (range, 55 to 90 years) and included 25 females (53.2%) and 22 males (46.8%). The control (nondementia) group (n = 49) had mean age of 75.18 ± 7.48 years (range, 55 to 89 years) and included 25 females (51.0%) and 24 males (49.0%) (Table 1). Although the control group was significantly older than the dementia group (t (94) = 2.12, p = 0.036), the mean age difference was modest. Since age-related structural brain atrophy is expected to be more pronounced in older individuals, this imbalance would not be expected to artificially inflate the observed diagnostic performance. Nevertheless, a potential influence of age-related brain changes on model output cannot be completely excluded. A chi-square test found no association between sex and dementia diagnosis (χ^2 = 0.045, p = 0.83).

We evaluated diagnostic performance with multiple metrics. Overall accuracy was 89.58% (95% CI, 81.88-94.24), indicating favorable diagnostic performance within this cohort for a single-sequence imaging model. Sensitivity was 78.70% (95% CI, 64.28-88.67). Specificity was 100.00% (95% CI, 92.75-100.00), with no false positives observed in this cohort (0/49). The PPV was 100.00% (95% CI, 90.51-100.00), reflecting

TABLE 1
Descriptive statistics of dementia and nondementia patients

	Dementia (n = 47)				Non-Dementia (n = 49)				
	n	%	Mean ± SD	Range	n	%	Mean ± SD	Range	*p*
Age (year)			71.76 ± 8.32	55-90			75.18 ± 7.48	55-89	0.036*
Sex									
Female	25	53.2			25	51.0			0.83**
Male	22	46.8			24	49.0			

SD, standard deviation; * t-test; ** chi-square test.

TABLE 2
Classification performance table for the AI model

AI diagnosis	Real diagnosis: Dementia (n)	Real diagnosis: Non-dementia (n)	Total
Dementia	37	0	37
Non-dementia	10	49	59
Total	**47**	**49**	**96**

Performance metric	Value (FLAIR MRI-based AI model)	95% CI
Accuracy (%)	89.6	81.88-94.24
Sensitivity (%)	78.7	64.28-88.67
Specificity (%)	100	92.75-100
Positive predictive value (%)	100	90.51-100
Negative predictive value (%)	83.1	71.63-90.8
F1 score	0.88	-

AI, artificial intelligence; MRI, magnetic resonance imaging; CI, confidence interval; F1 score: Harmonic mean of precision and recall.

that all AI-positive cases (37/37) were confirmed as dementia in this cohort. The NPV was 83.10% (95% CI, 71.63-90.83). The F1-score was 88.00% (Table 2).

The point-biserial correlation between the AI-derived dementia probability score and the reference diagnosis was r = 0.762 (95% CI, 0.65-0.85; $p < 0.001$). The Spearman correlation was ρ = 0.757 (95% CI, 0.64-0.85; $p < 0.001$), consistent in magnitude and direction. These results indicated a positive association between the AI probability score and the clinical diagnosis (Figure 1).

The McNemar test on discordant classifications was significant ($p = 0.00195$), reflecting a significant asymmetry between false negatives and false positives (n = 10 *vs.* n = 0) derived from the confusion matrix (Table 2). The Binomial test rejected the null hypothesis that overall accuracy equals 50% (observed 86/96 correct; accuracy 89.58%; $p < 0.001$). These results indicated that the observed classification performance was unlikely to be explained by chance alone.

Receiver operating characteristic analysis showed an AUC of 0.937 ($p < 0.001$). At the Youden threshold (0.43), sensitivity was 0.83, and specificity was 0.96 (Figure 2). This value was close to the predefined 50% cutoff used for classification, supporting the robustness of the chosen threshold.

DISCUSSION

From a clinical perspective, the primary contribution of this study lies in proposing a triage-oriented use of AI-derived probability outputs rather than a standalone diagnostic tool.

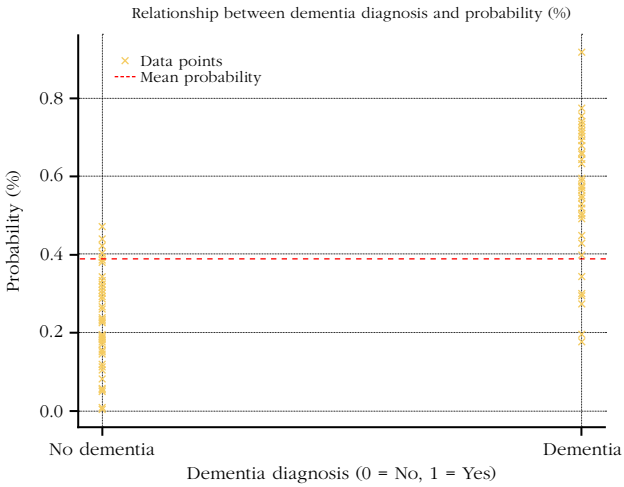

Figure 1. Scatterplot showing the relationship between clinical dementia diagnosis (0 = nondementia, 1 = dementia) and AI-derived dementia probability values. Each yellow marker represents an individual patient. The dashed red line indicates the mean probability across the cohort. The plot demonstrates clear separation of probability values between dementia and nondementia groups and shows the distribution across clinical categories; see Table 2.

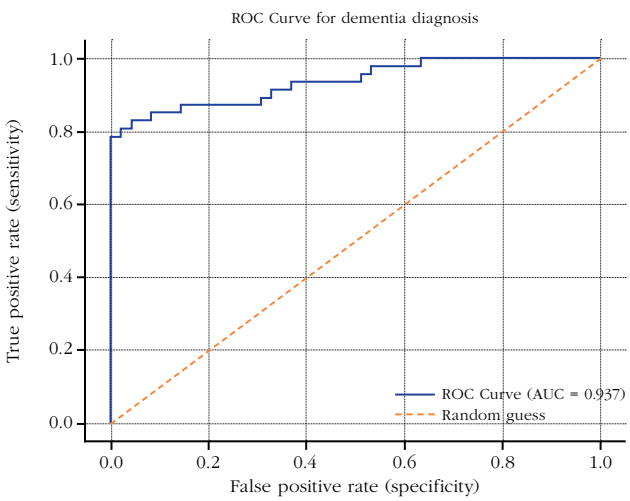

Figure 2. Receiver operating characteristic curve illustrating the discriminative performance of the AI-derived dementia probability score in distinguishing patients with dementia from controls. The AUC was 0.937, indicating strong diagnostic performance. The diagonal dashed line represents the performance of a random classifier (AUC = 0.5).

ROC, receiver operating characteristic; AUC, area under the curve; AI, artificial intelligence.

In this single-center cohort (n = 96), the AI-derived dementia probability score demonstrated promising discriminative performance (AUC = 0.937). Operating characteristics were as follows: specificity, 100.00%; PPV, 100.00%; and sensitivity, 78.70%, indicating that positive classifications are highly reliable, while sensitivity remains an area for improvement. Notably, the absence of false-positive cases in this cohort is consistent with the potential utility of the model as a rule-in decision-support tool, providing high diagnostic confidence when identifying patients who require further diagnostic work-up. Such a rule-in profile may be particularly valuable in clinical workflows, where unnecessary referrals can be minimized while ensuring that high-probability cases are appropriately prioritized. The strong positive correlations between the probability score and clinical diagnosis support the construct validity of the output. Additionally, McNemar and Binomial tests were significant, indicating that the observed classification pattern and overall accuracy were unlikely to be attributable to chance, further supporting the potential clinical applicability of the model. Collectively, these findings position the AI-generated probability as a practical adjunct in outpatient settings, although prospective multicenter and multisequence validation is warranted to enhance sensitivity and generalizability.

Despite the availability of advanced imaging modalities such as functional MRI, PET/MRI, and volumetric analyses, conventional structural MRI remains the standard first-line tool in the diagnostic work-up of dementia. In daily practice, radiologists rely on widely validated visual rating scales to recognize characteristic atrophy patterns: the medial temporal atrophy score for hippocampal and entorhinal involvement, the global cortical atrophy score for diffuse cortical changes, and the Koedam score for parietal atrophy. In addition, white matter hyperintensities on FLAIR are commonly graded using the Fazekas scale, which reflects the contribution of small-vessel disease. These scales have proven diagnostic and prognostic value; however, their routine use can be time-consuming and subject to interobserver variability. Our study builds on this context by showing that a previously published AI-based model, originally developed using T1-weighted MRI images, can generate a standardized dementia probability score when applied to routine FLAIR MRI examinations, thereby complementing traditional visual assessments in busy outpatient settings.[15-17] The use of a single routinely acquired FLAIR sequence represents a pragmatic design choice aimed at maximizing clinical applicability. Since FLAIR imaging is part of nearly all routine brain MRI protocols, this approach could be integrated into

routine workflows without additional acquisition time. Recent studies have also highlighted the growing role of MRI-based quantitative and computer-assisted approaches in the evaluation of dementia and cognitive impairment.[18]

Unlike most AI approaches that aim to deliver a categorical diagnosis or subtype classification, our model was designed to provide an immediately interpretable probability at the first clinical encounter. This triage-oriented output supports, but does not replace, clinical judgment by helping clinicians prioritize which patients should undergo comprehensive neuropsychological testing or advanced imaging. In practice, such a probability score could be integrated into the radiology workflow through PACS, offering near real-time feedback without prolonging reporting time. By focusing on a single, standardized probability derived from a widely available sequence, this approach emphasizes feasibility, speed, and reproducibility in routine neuroradiology practice.[19,20]

The use of routine FLAIR MRI in the present study should not be interpreted as evidence that T1-weighted and FLAIR sequences are interchangeable. The pretrained CNN evaluated in this study was originally developed using T1-weighted MRI images, whereas the present work investigated its performance on routinely acquired FLAIR examinations as a pragmatic real-world validation. This cross-sequence application may introduce domain shift, as the two MRI sequences depict different tissue characteristics. Nevertheless, both T1-weighted and FLAIR MRI depict macroscopic structural changes associated with neurodegeneration, particularly cerebral atrophy, which may partially explain the encouraging discriminative performance observed despite the sequence differences. The primary objective of this study was not to retrain or optimize the model for FLAIR imaging but to evaluate whether the previously published model could provide clinically useful performance under routine outpatient conditions.

Notably, the original study identified the lack of evaluation on real-world clinical data as one of its principal limitations. The present study was specifically designed to address this gap by evaluating the previously published pretrained CNN in an independent real-world outpatient cohort. Although encouraging diagnostic performance was observed, further external validation across multiple institutions and imaging protocols remains necessary before broader clinical implementation.

Beyond imaging-based analysis, an additional consideration is how such probability scores could interact with established clinical pathways, particularly neuropsychological testing, which remains the cornerstone for definitive diagnosis.

Neuropsychological testing remains the clinical cornerstone for confirming and staging cognitive-behavioral syndromes; however, its routine use in all outpatients is constrained by time, access, and cultural and educational variability. Current Alzheimer's Association guidance positions comprehensive neuropsychological evaluation as critical when office-based screening is inconclusive or cases are complex, supporting timely and accurate diagnosis, monitoring disease progression, and individualized care planning. However, in real-world clinics, where education level and cultural factors may influence the performance of brief screening tools, deploying full batteries for every referral is neither feasible nor efficient. In this context, our FLAIR-based, AI-derived dementia probability score is intended as a rapid triage signal that may help prioritize patients for comprehensive neuropsychological evaluation while reducing unnecessary testing in low-probability cases.[21-24]

The clinical implications of the observed diagnostic profile should be interpreted considering the intended use of the proposed model. Although false-negative classifications remain clinically important, the absence of false-positive classifications suggests that patients identified by the model as having a high probability of dementia are unlikely to undergo unnecessary additional investigations due to erroneous AI classification. Importantly, the proposed system was not designed to establish a definitive diagnosis or exclude dementia. Instead, it provides a probability-based decision-support output intended to assist clinicians in prioritizing patients for further diagnostic evaluation while complementing, rather than replacing, comprehensive clinical assessment and neuropsychological testing.

This study had several important limitations. First, its retrospective design may have introduced selection bias and limited control over case inclusion. Second, the sample size was relatively small (n = 96), which may restrict the generalizability of the findings. All MRI scans were obtained from a single center using a standardized 1.5 Tesla protocol. While this ensured consistency across

the dataset, it may limit applicability to different institutions, scanners, and acquisition settings. The reference standard was based on clinical diagnosis supported by neuropsychological testing without histopathological or biomarker confirmation. Furthermore, detailed etiological subtype information was not consistently available in this retrospective cohort. Therefore, subtype-specific analyses could not be performed, and the reported diagnostic performance should be interpreted for primary degenerative dementia as a whole, rather than for individual dementia subtypes. An additional methodological limitation is that the pretrained CNN was originally developed using an Alzheimer's disease T1-weighted MRI dataset, whereas the present study evaluated its performance on routinely acquired FLAIR MRI examinations. This cross-sequence application may have introduced domain shift since T1-weighted and FLAIR MRI sequences depict different tissue characteristics. Furthermore, the original study identified the absence of evaluation on real-world clinical data as one of its principal limitations. The present study was specifically designed to address this gap by evaluating the previously published model in an independent real-world clinical cohort. However, this should be regarded as an initial clinical validation rather than definitive evidence of generalizability. In addition, images were standardized using a uniform preprocessing pipeline, which may have introduced minor resampling effects. Model calibration was not formally assessed and should be evaluated in future studies. Finally, external prospective validation in larger, multicenter, and unselected clinical populations remains necessary to confirm the robustness, calibration, and clinical applicability of the proposed approach. Despite these limitations, our findings demonstrated the feasibility of applying a previously published AI model to routine FLAIR MRI examinations in a real-world clinical setting, suggesting a potential role for AI-driven probability outputs in streamlining dementia evaluation pathways.

In conclusion, an AI-derived dementia probability score from routine FLAIR MRI demonstrated promising discriminative ability and findings consistent with potential rule-in utility. These findings suggest its potential role as a decision support tool rather than a standalone diagnostic method. Integration of such probability outputs into clinical workflows may facilitate patient triage and optimize the use of neuropsychological testing. However, prospective multicenter validation and integration of multisequence MRI data are required to confirm generalizability and improve sensitivity.

Data Sharing Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Author Contributions: Ş.B.A.: Designed the study, collected and curated the imaging data, performed the statistical analysis, and wrote the manuscript; A.B.: Identified and clinically evaluated the patients diagnosed with dementia.: M.Ş.: Developed the artificial intelligence model and provided technical support for its implementation; G.Ş.: Supervised the study and coordinated the collaboration between clinical and engineering components. All authors reviewed the manuscript, contributed to its revision, and approved the final version.

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