# <u>ACK 2024학술발표대회 논문집 (31권 2호)</u><br>알츠하이머병 예후 예측: MRI 및 메타데이터를<br>활용한 MMSE 점수 예측 모델 알츠하이머병 예후 예측: MRI 및 메타데이터를 드 예측: MRI 및 메<mark>E</mark><br>MSE 점수 예측 모<br>, <sub>문소연<sup>2</sup>, 송여경<sup>3,</sup> 장지우<sup>3</sup><br>!교 의과대학 의학과 학부생</sub>

조채은<sup>1</sup>, 문소연<sup>2</sup>, 송여경<sup>3,</sup> 장지우<sup>3</sup>  $1$ 고려대학교 의과대학 의학과 학부생  $2$ 경성대학교 컴퓨터공학과 학부생  $^3$ 성신여자대학교 AI융합학부 학부생 조채은<sup>1</sup>, 문소연<sup>2</sup>, 송여경<sup>3,</sup> 장지우<sup>3</sup><br><sup>1</sup>고려대학교 의과대학 의학과 학부생<br><sup>2</sup>경성대학교 컴퓨터공학과 학부생<br><sup>3</sup>성신여자대학교 AI융합학부 학부생<br>chochaeeun@korea.ac.kr, opir0oui@gmail.com,<br>llengef0802@gmail.com, jangjang0022@naver.com  $1\overline{u}$ 려대학교 의과대학 의학과 학부생<br><sup>2</sup>경성대학교 컴퓨터공학과 학부생<br><sup>3</sup>성신여자대학교 AI융합학부 학부생<br>chochaeeun@korea.ac.kr, opir0oui@gmail.com,<br>challengef0802@gmail.com, jangjang0022@naver.com 조채은<sup>1</sup>, 문소연<sup>2</sup>, 송여경<sup>3,</sup> 장지우<sup>3</sup><br><sup>1</sup>고려대학교 의과대학 의학과 학부생<br><sup>2</sup>경성대학교 컴퓨터공학과 학부생<br><sup>3</sup>성신여자대학교 AI융합학부 학부생<br>chochaeeun@korea.ac.kr, opir0oui@gmail.com,<br>challengef0802@gmail.com, jangjang0022@naver.com<br>Prognosis Prediction of Alzheime

## $\begin{array}{c} ^1$ 고려대학교 의과대학 의학과 학부생<br>  $^2$ 경성대학교 컴퓨터공학과 학부생<br>  $^3$ 성식자대학교 AI융합학부 학부생<br>
chochaeeun@korea.ac.kr, opir0oui@gmail.com,<br>
challengef0802@gmail.com, jangjang0022@naver.com<br>
Prognosis Prediction of Alzheimer's Disease:<br>
Mul Metadata i-Horizon MMSE Prediction from MRI and<br>Metadata<br>Chaeeun Cho<sup>1</sup>, Soyeon Moon<sup>2</sup>, Yeogyeong Song<sup>3</sup>, Jiwoo Jang<sup>3</sup><br><sup>1</sup>Dept. of Medicine. Korea University College of Medicine HOMET MINSE Prediction from MRI and<br>Metadata<br>naeeun Cho<sup>1</sup>, Soyeon Moon<sup>2</sup>, Yeogyeong Song<sup>3</sup>, Jiwoo Jang<sup>3</sup><br><sup>1</sup>Dept. of Medicine, Korea University College of Medicine<br><sup>2</sup>Dept. of Computer Engineering, Kyungsung University

**Metadata**<br>
aeeun Cho<sup>1</sup>, Soyeon Moon<sup>2</sup>, Yeogyeong Song<sup>3</sup>, Jiwoo Jang<sup>3</sup><br>
Dept. of Medicine, Korea University College of Medicine<br>
<sup>2</sup>Dept. of Computer Engineering, Kyungsung University<br>
School of AI Convergence, Sungshi INCLACALA<br>
haeeun Cho<sup>1</sup>, Soyeon Moon<sup>2</sup>, Yeogyeong Song<sup>3</sup>, Jiwoo Jang<sup>3</sup><br>
<sup>1</sup>Dept. of Medicine, Korea University College of Medicine<br>
<sup>2</sup>Dept. of Computer Engineering, Kyungsung University<br>
<sup>3</sup>School of AI Convergence, S

### Summary

<sup>2</sup>Dept. of Computer Engineering, Kyungsung University<br><sup>3</sup>School of AI Convergence, Sungshin Women's University<br>Summary<br>This study aims to predict MMSE scores in Alzheimer's disease (AD) patients using a<br>NN-LSTM model that <sup>3</sup>School of AI Convergence, Sungshin Women's University<br>
Summary<br>
This study aims to predict MMSE scores in Alzheimer's disease (AD) patients using a<br>
CNN-LSTM model that processes MRI images and metadata. The OASIS-2 da Summary<br>
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CNN-LSTM model that processes MRI images and metadata. The OASIS-2 dataset was used,<br>
with MRI slices (central, ±10mm, and ±15mm) and metadata. Two datasets were created: one<br>
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with central and ±10mm slice This study aims to predict M.<br>CNN-LSTM model that processes<br>with MRI slices (central, ±10mm,<br>with central and ±10mm slices (1<br>slices (combined dataset).<br>The CNN-LSTM model extractes This study aims to predict MMSE scores in Alizhelmer's disease (AD) patients using a<br>
NN-LSTM model that processes MRI images and metadata. The OASIS-2 dataset was used,<br>
with MRI slices (central,  $\pm 10\text{mm}$ , and  $\pm 15$ CNN-LSTM model that processes MRI images and metadata. The OASIS-2 dataset was used, with MRI slices (central,  $\pm 10$ mm, and  $\pm 15$ mm) and metadata. Two datasets were created: one with central and  $\pm 10$ mm slices (10mm

The CNN-LST<br>predict MMSE s<br>0.527 and MAE<br>MRI and metada<br>1. Introduction<br>41zheimer/s disease predict MMSE scores. The 10mm model outperformed the combined model, achieving an MSE of<br>
0.527 and MAE of 0.509. This study highlights the potential of predicting MMSE scores using<br>
MRI and metadata for early diagnosis of GG16 and combined them with metadata to<br>1 the combined model, achieving an MSE of<br>potential of predicting MMSE scores using<br>MRI, offering more accurate prognosis predictions<br>and supporting early interventions. Ultimately, with MRI shces (central, ±10mm, and ±15mm) and metadata. Two datasets were created one<br>with central and ±10mm slices (10mm dataset), and another with central, ±10mm, and ±15mm<br>slices (combined dataset).<br>The CNN-LSTM model With central and ±10mm slices (10mm dataset), and anot<br>slices (combined dataset).<br>The CNN-LSTM model extracted features using VGG16<br>predict MMSE scores. The 10mm model outperformed the<br>0.527 and MAE of 0.509. This study hi

MRI and metadata for early diagnosis of AD.<br> **1. Introduction** MRI, offe<br>
Alzheimer's disease (AD) is a neurodegenerative and support<br>
disorder where early diagnosis is critical to approach<br>
improving patient outcomes With 1. Introduction MRI, Maximum MRI, Alzheimer's disease (AD) is a neurodegenerative and states and states of the disorder where early diagnosis is critical to approach in approximation accurate programs are prediction is **1. Introduction**<br>
Alzheimer's disease (AD) is a neurodegenerative and suppo<br>
disorder where early diagnosis is critical to approach<br>
improving patient outcomes. With an aging patient ou<br>
population, accurate prognosis pre Alzheimer's disease (AD) is a neurodegenerative<br>disorder where early diagnosis is critical to<br>improving patient outcomes. With an aging<br>population, accurate prognosis prediction is<br>increasingly important for timely interve disorder where early diagnosis is critical to applies<br>improving patient outcomes. With an aging parapopulation, accurate prognosis prediction is<br>increasingly important for timely intervention. 2.<br>Current research focuses o mproving patient outcomes. With an aging patient<br>population, accurate prognosis prediction is<br>increasingly important for timely intervention. **2. N**<br>Current research focuses on MRI-based Th<br>diagnostics combined with metad propulation, accurate prognosis prediction is<br>increasingly important for timely intervention.<br>Current research focuses on MRI-based<br>diagnostics combined with metadata to improve<br>predictive accuracy[1].<br>The Mini-Mental Stat The Mini-Mental State Examination (MMSE) is<br>
widely used tool for detecting comitive decline Current research focuses on MRI-based The<br>diagnostics combined with metadata to improve MMS<br>predictive accuracy[1]. from<br>The Mini-Mental State Examination (MMSE) is mode<br>a widely used tool for detecting cognitive decline,

diagnostics combined with metadata to improve MMS<br>predictive accuracy[1]. from<br>The Mini-Mental State Examination (MMSE) is mode<br>a widely used tool for detecting cognitive decline, featu<br>with studies showing that a drop in rrom<br>The Mini-Mental State Examination (MMSE) is mode<br>a widely used tool for detecting cognitive decline, feature<br>with studies showing that a drop in MMSE comb<br>scores often precedes frontal lobe atrophy, making time<br>it val The Mini-Mental State Examination (MM<br>a widely used tool for detecting cognitive<br>with studies showing that a drop in<br>scores often precedes frontal lobe atrophy, i<br>it valuable for diagnosing AD[2]. widely used tool for detecting cognitive decline, teature<br>
with studies showing that a drop in MMSE combine<br>
cores often precedes frontal lobe atrophy, making time-ser<br>
valuable for diagnosing AD[2]. 2.1. Dat<br>
This study a with studies showing that a drop in MMSE combine<br>scores often precedes frontal lobe atrophy, making time-se<br>it valuable for diagnosing AD[2]. **2.1. Da**<br>This study aims to develop a model that The C<br>forecasts MMSE scores at

scores often precedes frontal lobe atrophy, making<br>it waluable for diagnosing AD[2].<br>**2.1. Data Collection and Preprocessing**<br>This study aims to develop a model that The OASIS-2 dataset was used, and MRI slices<br>forecasts M it valuable for diagnosing AD[2]. **2.1. Data**<br>
This study aims to develop a model that The OA<br>
forecasts MMSE scores at the next clinical visit (central,<br>
by combining metadata with multiple MRI slices. 256x256 j<br>
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potential of predicting MMSE scores using<br>potential of predicting MMSE scores using<br>MRI, offering more accurate prognosis predictions<br>and supporting early interventions. Ultimately, this<br>approach sims to improve early diag MRI, offering more accurate prognosis predictions<br>and supporting early interventions. Ultimately, this<br>approach aims to improve early diagnosis and<br>patient outcomes in clinical practice MRI, offering more accurate prognosis predicand supporting early interventions. Ultimately approach aims to improve early diagnosis patient outcomes in clinical practice. Superoach aims to improve early diagnosis and patient outcomes in clinical practice.<br> **2. Method**<br>
The aim of this study is to predict future pproach aims to improve early diagnosis and<br>atient outcomes in clinical practice.<br>**Nethod**<br>The aim of this study is to predict future<br>MASE scores using MBI images and metadata

MMSE scores using MRI images and metadata **2. Method**<br>The aim of this study is to predict future<br>MMSE scores using MRI images and metadata<br>from previous clinical visits. A CNN-LSTM<br>model was developed with VGG16 used for **2. Method**<br>
The aim of this study is to predict future<br>
MMSE scores using MRI images and metadata<br>
from previous clinical visits. A CNN-LSTM<br>
model was developed, with VGG16 used for<br>
feature extraction from MRI images an The aim of this study is to predict future<br>MMSE scores using MRI images and metadata<br>from previous clinical visits. A CNN-LSTM<br>model was developed, with VGG16 used for<br>feature extraction from MRI images, and the<br>combined f MMSE scores using MRI images and metadata<br>from previous clinical visits. A CNN-LSTM<br>model was developed, with VGG16 used for<br>feature extraction from MRI images, and the<br>combined features and metadata processed in a<br>time-se model was developed, with VGG16 used for<br>feature extraction from MRI images, and the<br>combined features and metadata processed in a feature extraction from MRI images, and the eature extraction from MRI images, and the<br>ombined features and metadata processed in a<br>ime-series structure to predict MMSE scores.<br>**.1. Data Collection and Preprocessing**<br>The OASIS-2 dataset was used, and MRI slices<br>cent

combined features and metadata processed in a<br>time-series structure to predict MMSE scores.<br>2.1. Data Collection and Preprocessing<br>The OASIS-2 dataset was used, and MRI slices<br>(central, ±10mm, and ±15mm) were resized to<br>25 time-series structure to predict MMSE scores.<br> **2.1. Data Collection and Preprocessing**<br>
The OASIS-2 dataset was used, and MRI slices<br>
(central, ±10mm, and ±15mm) were resized to<br>
256x256 pixels and converted into RGB for 2.1. Data Collection and Preprocessing<br>The OASIS-2 dataset was used, and MRI slices<br>(central,  $\pm 10$ mm, and  $\pm 15$ mm) were resized to<br>256x256 pixels and converted into RGB for CNN<br>input. Two datasets were created: one c

 $\frac{\text{ACK 2024}}{\text{ACK 2024}} \pm \frac{\text{E}}{\text{E}}$  (3)<br>the central slice and slices from the  $\pm 10$ mm  $\pm 10$ mm<br>range(10mm dataset) and another including slices MSE of  $\frac{\text{ACK 2024}}{\text{X2024}} = \frac{\text{ACK 2024}}{\text{X2024}} = \frac{\text{ACK 2024}}{\text{X2024}} = \frac{\text{L}}{\text{E}}$ <br>
the central slice and slices from the  $\pm 10\text{mm}}$   $\pm 10\text{mm}$   $\pm 10\text{mm}$   $\pm 10\text{mm}$   $\pm 10\text{mm}$   $\pm 15\text{mm}$   $\pm 10\text{mm}$   $\pm 15\text{mm$ the central slice and slices from the ±10mm ±10m<br>
range(10mm dataset), and another including slices MSE<br>
from both the ±10mm and ±15mm ranges The<br>
(combined dataset) Metadata including age sex most the central slice and slices from the  $\pm 10$ mm  $\pm 10$ mm range(10mm dataset), and another including slices MSE of from both the  $\pm 10$ mm and  $\pm 15$ mm ranges The 1(combined dataset). Metadata, including age, sex, most r the central slice and slices from the  $\pm 10$ mm  $\pm 10$ mm range(10mm dataset), and another including slices MSE of from both the  $\pm 10$ mm and  $\pm 15$ mm ranges The 10 (combined dataset). Metadata, including age, sex, most range(10mm dataset), and another including slices  $MSE$ <br>from both the  $\pm 10$ mm and  $\pm 15$ mm ranges The<br>(combined dataset). Metadata, including age, sex, most<br>education level, SES, and CDR scores, was scores<br>normalized an from both the  $\pm 10$ mm and  $\pm 15$ mm ranges<br>(combined dataset). Metadata, including age, sex,<br>education level, SES, and CDR scores, was<br>normalized and matched with MRI for each visit.<br>**2.2. Model Architecture**<br>The CNN-LS combined dataset). Metadata, including age, sex, most r<br>ducation level, SES, and CDR scores, was scores.<br>ormalized and matched with MRI for each visit. errors,<br>2. Model Architecture<br>The CNN-LSTM model processed both MRI

education level, SES, and CDR scores, was scored and matched with MRI for each visit. er<br> **2.2. Model Architecture**<br>
The CNN-LSTM model processed both MRI<br>
images and metadata for MMSE score prediction. normalized and matched with MRI for each visit. errors,<br>
2.2. Model Architecture<br>
The CNN-LSTM model processed both MRI<br>
images and metadata for MMSE score prediction.<br>
Features from MRI images were extracted using<br>
a pret 2.2. Model Architecture<br>
The CNN-LSTM model processed both MRI<br>
images and metadata for MMSE score prediction.<br>
Features from MRI images were extracted using<br>
a pretrained VGG16 model with imagenet weights,<br>
where the top The CNN-LSTM model processed both MRI<br>
images and metadata for MMSE score prediction.<br>
Features from MRI images were extracted using<br>
a pretrained VGG16 model with imagenet weights,<br>
where the top classification layers wer mages and metadata for MMSE score prediction.<br>
Features from MRI images were extracted using<br>
a pretrained VGG16 model with imagenet weights,<br>
where the top classification layers were removed,<br>
and a Flatten layer was add Features from MRI images were extracted using<br>
a pretrained VGG16 model with imagenet weights,<br>
where the top classification layers were removed,<br>
and a Flatten layer was added to convert the<br>
features into 1-dimensional v a pretrained VGG16 model with imagenet weights,<br>where the top classification layers were removed,<br>and a Flatten layer was added to convert the<br>features into 1-dimensional vectors. These<br>features were passed through a Time where the top classification layers were removed,<br>
and a Flatten layer was added to convert the<br>
features into 1-dimensional vectors. These<br>
features were passed through a Time Distributed<br>
layer to handle the sequential n Features into 1-dimensional vectors. These<br>
features were passed through a Time Distributed<br>
layer to handle the sequential nature of the data.<br>
Metadata, including age, sex, and CDR scores,<br>
was processed in parallel and reatures into 1-dimensional vectors. These<br>features were passed through a Time Distributed<br>layer to handle the sequential nature of the data.<br>Metadata, including age, sex, and CDR scores,<br>was processed in parallel and comb teatures were passed through a Time Distributed<br>
layer to handle the sequential nature of the data.<br>
Metadata, including age, sex, and CDR scores,<br>
was processed in parallel and combined with the<br>
image features through a Expect to handle the sequential nature of the data.<br>
Metadata, including age, sex, and CDR scores,<br>
was processed in parallel and combined with the<br>
image features through a Concatenate layer. The<br>
combined data was then p Metadata, including age, sex, and CDR scores,<br>was processed in parallel and combined with the<br>image features through a Concatenate layer. The<br>combined data was then passed to an LSTM<br>layer with 50 units, using the ReLU act was processed in parallel and combined with the<br>
image features through a Concatenate layer. The<br>
combined data was then passed to an LSTM<br>
layer with 50 units, using the ReLU activation<br>
function to capture temporal depen Final prediction layer, with a single neuron,<br>
final prediction layer, with a single neuron,<br>
final prediction layer, with a single neuron,<br>
final prediction layer, with a single neuron,<br>  $\frac{1}{2}$  in specific areas, perfo combined data was then passed to an LSTM<br>layer with 50 units, using the ReLU activation<br>function to capture temporal dependencies. The<br>final prediction layer, with a single neuron,<br>employed a linear activation function to layer with 50 units, using the H<br>function to capture temporal dep<br>final prediction layer, with a<br>employed a linear activation functic<br>predicted MMSE score.<br>2.3 Model Training and Evaluat tunction to capture temporal dependencies.<br>
final prediction layer, with a single neu<br>
employed a linear activation function to output<br>
predicted MMSE score.<br> **2.3. Model Training and Evaluation**<br>
The model was trained usi mal prediction layer, with a single neuron, in spec<br>mployed a linear activation function to output the patient<br>redicted MMSE score.<br>**3. Model Training and Evaluation** the patient<br>The model was trained using the Adam consis

employed a linear activation function to output the<br>predicted MMSE score.<br> **2.3. Model Training and Evaluation** the pati<br>
The model was trained using the Adam<br>
optimizer with a learning rate of 0.0001, and then s<br>
Mean Squ predicted MMSE score.<br> **2.3. Model Training and Evaluation** the pation<br>
optimizer with a learning rate of 0.0001, and when special Mean Squared Error (MSE) was used as the loss images<br>
function Early stopping and ModelChec **2.3. Model Training and Evaluation**<br>The model was trained using the Adam<br>optimizer with a learning rate of 0.0001, and<br>Mean Squared Error (MSE) was used as the loss<br>function. Early stopping and ModelCheckpoint<br>callbacks w The model was trained using the Adam<br>
optimizer with a learning rate of 0.0001, and<br>
Mean Squared Error (MSE) was used as the loss<br>
function. Early stopping and ModelCheckpoint<br>
callbacks were applied to store the further<br> Function. Early stopping and ModelCheckpoint<br>callbacks were applied to store the<br>best-performing model. The 10mm and combined<br>datasets were split 80-20 for training and testing. Mean Squared Error (MSE) was used as the loss<br>function. Early stopping and ModelCheckpoint<br>callbacks were applied to store the<br>best-performing model. The 10mm and combined<br>datasets were split 80-20 for training and testing tunction. Early stopping and ModelCheckpoint<br>
callbacks were applied to store the<br>
best-performing model. The 10mm and combined<br>
datasets were split 80-20 for training and testing.<br>
The performance of both models was eval callbacks were applied to store the<br>best-performing model. The 10mm and combined<br>datasets were split 80-20 for training and testing.<br>The performance of both models was evaluated<br>using MSE and Mean Absolute Error (MAE). The performance of both models was evaluated<br>using MSE and Mean Absolute Error (MAE).<br>3. Results<br>We developed and evaluated an MMSE score The performance of both models was evaluated<br>
sing MSE and Mean Absolute Error (MAE).<br>  $\begin{array}{ccc}\n\text{H} & \text{H} \\
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using MSE and Mean Absolute Error (MAE).<br>3. **Results**<br>We developed and evaluated an MMSE score<br>prediction model for early diagnosis of [1] Sama<br>Alzheimer's disease by combining two different trajectorie **E**<br> **E**<br>
We developed and evaluated an MMSE score<br>
prediction model for early diagnosis of<br>
Alzheimer's disease by combining two different<br>
MRI multi-slice configurations with metadata The<br>
Scie 3. Hesuits<br>
We developed and evaluated an MMSE score<br>
prediction model for early diagnosis of<br>
Alzheimer's disease by combining two different<br>
MRI multi-slice configurations with metadata. The<br>
model using central slices a We developed and evaluated an MMSE score<br>prediction model for early diagnosis of trajectori<br>Alzheimer's disease by combining two different<br>MRI multi-slice configurations with metadata. The<br>model using central slices at ±10 prediction model for early diagnosis of trajector<br>Alzheimer's disease by combining two different Scienti:<br>MRI multi-slice configurations with metadata. The<br>model using central slices at  $\pm 10$ mm from the Useful<br>midline (1 Alzheimer's disease by combining two different<br>MRI multi-slice configurations with metadata. The<br>model using central slices at ±10mm from the<br>midline (10mm model) achieved an MSE of 0.527<br>and an MAE of 0.509. The model usi

<del>논문</del>집(31권 2호)<br>±10mm and ±15mm (combined model) showed an<br>MSE of 0.849 and an MAE of 0.562  $\pm 10$ mm and  $\pm 15$ mm (combined model) showed an MSE of 0.849 and an MAE of 0.562.  $10$ mm and  $\pm 15$ mm (combined model) showed an<br>
ISE of 0.849 and an MAE of 0.562.<br>
The 10mm model showed greater accuracy, with<br>
nost residuals within  $+1$  of the actual MMSE

 $\pm 10$ mm and  $\pm 15$ mm (combined model) showed an<br>MSE of 0.849 and an MAE of 0.562.<br>The 10mm model showed greater accuracy, with<br>most residuals within  $\pm 1$  of the actual MMSE<br>scores. In contrast, the combined model had  $\pm$ 10mm and  $\pm$ 15mm (combined model) showed an<br>MSE of 0.849 and an MAE of 0.562.<br>The 10mm model showed greater accuracy, with<br>most residuals within  $\pm$ 1 of the actual MMSE<br>scores. In contrast, the combined model had la MSE of 0.849 and an MAE of 0.562.<br>The 10mm model showed greater accuracy, with<br>most residuals within  $\pm 1$  of the actual MMSE<br>scores. In contrast, the combined model had larger<br>errors, especially in lower MMSE scores.



Fig 1.  $10mm(left)$  and combined $(right)$  model ig 1. I0mm(left) and combined(right) model<br>IMSE prediction at each visit<br>Conclusions<br>This study demonstrates the potential of<br>redicting MMSE scores using multi-slice MRI

MMSE prediction at each visit<br> **4. Conclusions**<br>
This study demonstrates MMSE prediction at each visit<br> **4. Conclusions**<br>
This study demonstrates the potential of<br>
predicting MMSE scores using multi-slice MRI<br>
images and metadata indicating the possibility of 4. Conclusions<br>
This study demonstrates the potential of<br>
predicting MMSE scores using multi-slice MRI<br>
images and metadata, indicating the possibility of<br>
early diagnosis and intervention for Alzbeimer's This study demonstrates the potential of predicting MMSE scores using multi-slice MRI images and metadata, indicating the possibility of early diagnosis and intervention for Alzheimer's This study demonstrates the potential of<br>predicting MMSE scores using multi-slice MRI<br>images and metadata, indicating the possibility of<br>early diagnosis and intervention for Alzheimer's<br>disease. The 10mm model showed more predicting MMSE scores using multi-slice MRI<br>images and metadata, indicating the possibility of<br>early diagnosis and intervention for Alzheimer's<br>disease. The 10mm model showed more stability<br>and consistency, especially at mages and metadata, indicating the possibility of<br>early diagnosis and intervention for Alzheimer's<br>disease. The 10mm model showed more stability<br>and consistency, especially at extreme MMSE<br>scores, while the combined model early diagnosis and intervention for Alzheimer's<br>disease. The 10mm model showed more stability<br>and consistency, especially at extreme MMSE<br>scores, while the combined model was more<br>accurate in the mid-range but had larger disease. The 10mm model showed more stability<br>and consistency, especially at extreme MMSE<br>scores, while the combined model was more<br>accurate in the mid-range but had larger errors<br>in specific areas, performing better for p and consistency, especially at extreme MMSE<br>scores, while the combined model was more<br>accurate in the mid-range but had larger errors<br>in specific areas, performing better for particular<br>patient groups. These findings sugge scores, while the combined model was more<br>accurate in the mid-range but had larger errors<br>in specific areas, performing better for particular<br>patient groups. These findings suggest that both<br>the patient's condition and the accurate in the mid-range but had larger errors<br>in specific areas, performing better for particular<br>patient groups. These findings suggest that both<br>the patient's condition and the balance between<br>consistency and precision in specific areas, performing better for particular<br>patient groups. These findings suggest that both<br>the patient's condition and the balance between<br>consistency and precision should be considered<br>when selecting a model. Me patient groups. These findings suggest that both<br>the patient's condition and the balance between<br>consistency and precision should be considered<br>when selecting a model. Metadata and MRI<br>images remain critical predictors of the patient's condition and the balance between<br>consistency and precision should be considered<br>when selecting a model. Metadata and MRI<br>images remain critical predictors of Alzheimer's<br>progression, and future studies will consistency and precision should be considered<br>when selecting a model. Metadata and MRI<br>images remain critical predictors of Alzheimer's<br>progression, and future studies will focus on<br>collaborating with clinicians to refine when selecting a model. Metadata and MRI<br>images remain critical predictors of Alzheimer's<br>progression, and future studies will focus on<br>collaborating with clinicians to refine datasets and<br>further improve model performance application.

본 논문은 과학기술정보통신부 대학디지털교육역량 강화사업의 지원을 통해 수행한 ICT멘토링 프로젝 트 결과물입니다. 본 논문은 과악기술성보농신무 내악니시틸교육역당<br>강화사업의 지원을 통해 수행한 ICT멘토링 프로젝<br>트 결과물입니다.<br>**References**<br>[1] Samaneh A. Mofrad, "Cognitive and MRI<br>trajectories for prediction of Alzheimer's disease"

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