<u>ACK 2024학술발표대회 논문집 (31권 2호)</u>
SMOTE-ADNet: 향상된 CNN 과 SMOTE 를 활용한
알츠하이머병 및 초기 단계 정확한 분류 <u>ACK 2024 학술발표대회 논문집 (31권 2호)</u>
OTE-ADNet**: 향상된 CNN 과 SMOTE 를 활용한**
알츠하이머병 및 초기 단계 정확한 분류
^{손소영 ', 추현승[?]
'성균관대학교 전자전기컴퓨터공학과 박사과정} ACK 2024학술발표대회 논문집 (31권 2호)
DNet : 향상된 CNN 과 SMOTE 를 활용한
- 아이머병 및 초기 단계 정확한 분류
- 손소영 : 추현승 [?]
"성균관대학교 전자전기컴퓨터공학과 박사과정
"성균관대학교 전자전기컴퓨터공학과 교수 ACK 2024학술발표대회 논문집 (31권 2호)
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alvy.sun@g.skku.edu, choo@skku.edu 향상된 CNN과 SMOTE를 활용한
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_{대학교 전자전기컴퓨터공학과 박사과정
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everaging Enhanced CNN and SMOT]}} <u>ACK 2024 학술발표대회 논문집 (31권 2호)</u>
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"MOTE-ADNet Leveraging Enhanced CNN and SMOTE for
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SMOTE-ADNet Leveraging Enhanced CNN and SMOTE fo}

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**TE-ADNet Leveraging Enhanced CNN and SMOTE for
te Classification of Alzheimer's Disease and Early Stages**
Sun Xiaoying¹, Hyuns

Abstract

SMOTE-ADNet Leveraging Enhanced CNN and SMOTE for
Accurate Classification of Alzheimer's Disease and Early Stages
Sun Xiaoying¹, Hyunseung Choo¹
¹ Dept. of Electrical and Computer Engineering, Sungkyunkwan University SMOTE-ADNet Leveraging Enhanced CNN and SMOTE for

Accurate Classification of Alzheimer's Disease and Early Stages

Sun Xiaoying¹, Hyunseung Choo¹

¹Dept. of Electrical and Computer Engineering, Sungkyunkwan Universi **Accurate Classification of Alzheimer's Disease and Early Stages**

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 Abstract

Alzheimer's disease (AD) is a p Ends and Examples of the Summann Carry Stages

Sum Xiaoying¹, Hyunseung Choo¹

¹ Dept. of Electrical and Computer Engineering, Sungkyunkwan University
 Alzheimer's disease (AD) is a progressive neurodegenerative di Sun Xiaoying¹, Hyunseung Choo¹
¹ Dept. of Electrical and Computer Engineering, Sungkyunkwan University
Abstract
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This study presents SMOTE-ADNet, an innovative Convolutional Neural Network (CNN Sun Xiaoying¹, Hyunseung Choo¹

¹ Dept. of Electrical and Computer Engineering, Sungkyunkwan University
 Abstract

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by gradual cogn ¹ Dept. of Electrical and Computer Engineering, Sungkyunkwan University
 Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by gradual cognitive decline

and memory loss, with subtle cha **Examplementation**
 Examplementation Abstract
 Examplementation and memory loss, with subtle changes in brain structure that make accurate classification particularly challenging.

This study presents SMOTE-ADNet, an i **Abstract**
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and memory loos, with subtle changes in brain structure that make accurate classification particularly challen and memory loss, with subtle changes in brain structure that make accurations in the study presents SMOTE-ADNet, an innovative Convolutional N

enhance classification performance for Alzheimer's disease by integr

Syntheti Interaction persents SMOTE-AD

enhance classification performance

Synthetic Minority Over-samplin

convolutional layers, dropout regu

at differentiating between five sta

Early Mild Cognitive Impairment

Impairment (MCI) Synthetic Minority Over-sampling Technique (SMOTE). The SMOTE-ADNet architect
convolutional layers, dropout regularization, and a final dense layer optimized for multi-clas
at differentiating between five stages of Alzheim convolutional layers, dropout regularization, and a final dense layer optimized for multi-class cl

at differentiating between five stages of Alzheimer's disease: Alzheimer's disease (AD), Cogni

Early Mild Cognitive Impai at differentiating between five stages of Alzheimer's disease: Alzheimer's disease (AD), Co

Early Mild Cognitive Impairment (EMCI), Late Mild Cognitive Impairment (LMCI),

Impairment (MCI). Given the challenge of distingu folutional Neural Network (CNN) model designed to
the by integrating advanced CNN techniques with the
The SMOTE-ADNet architecture includes multiple
see layer optimized for multi-class classification, aimed
e: Alzheimer's is by integrating advanced CNN techniques with the
The SMOTE-ADNet architecture includes multiple
se layer optimized for multi-class classification, aimed
e: Alzheimer's disease (AD), Cognitive Normal (CN),
Cognitive Impai my optimized of mind-class casssince
and Alzheimer's disease (AD), Cognitive Normal (CN),
gnitive Impairment (LMCI), and Mild Cognitive
veen subtle variations in brain structure during these
g SMOTE and leverages advanced

Early Mild Cognitive Impairment (EMCI), Late Mild Cognitive Impairment (LM

Impairment (MCI). Given the challenge of distinguishing between subtle variations in

stages, SMOTE-ADNet effectively balances the dataset using S Impairment (MCI). Given the challenge of distinguishing between subtle variations in brackages, SMOTE-ADNet effectively balances the dataset using SMOTE and leverages attributed attributed of classifying subtle structural stages, SMOTE-ADNet effectively balances the dataset using SMOTE and leverages a achieve a remarkable accuracy of 98%. This result demonstrates the model's capability difficulty of classifying subtle structural differences empleta remarkable accuracy of 98%. Inis result demonstrates the models capability to
difficulty of classifying subtle structural differences and its potential for improving diagnostic
early intervention in Alzheimer's di intervention in Alzheimer's disease.
 1. Introduction
 1. Introduct 1. Introduction

Alzheimer's disease (AD) is a progressive neuro

degenerative disorder and the most common cause of

dementia, affecting millions of people worldwide. As of 2020,

Necent advances in

over 55 million peopl 1. Introduction

alzheimer's disease (AD) is a progressive neuro

degenerative disorder and the most common cause of

systems.

dementia, affecting millions of people worldwide. As of 2020,

Recent advances in artificial
 Example 10 to detect. Into an alternative disease (AD) is a progressive neuro particularly challeng degenerative disorder and the most common cause of systems.

dementia, affecting millions of people worldwide. As of 202 Alzheimer's disease (AD) is a progressive neuro particularly chalenging for bo
generative disorder and the most common cause of systems.
mentia, affecting millions of people worldwide. As of 2020,
recent advances in artif degenerative disorder and the most common cause of systems.

dementia, affecting millions of people worldwide. As of 2020, Recent advances in artific

over 55 million people globally were living with dementia, learning hav dementia, affecting millions of people worldwide. As of 2020,

over 55 million people globally were living with dementia,

with the majoristic and lower and the subtle and gradual onset of

By 2050,this number is projected over 55 million people globally were living with dementia,

with the majority of cases attributed to Alzheimer's disease.

By 2050,this number is projected to reach nearly 139 million, become a popular choice

emphasizing with the majority of cases attributed to Alzheimer's disease. The appear and By 2050, this number is projected to reach nearly 139 million, become a popular emphasizing the urgent need for early detection and classificatio

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escome a popuar en

emphasizing the urgent need for early detection and

intervention (Alzheimer's Disease and Dementia). Early and

acterns in data. However emphasizing the urgent need for early detection and classification due to their
intervention (Alzheimer's Disease and Dementia). Early and patterns in data. However,
accurate diagnosis is crucial for delaying disease progr

systems.

Cognitive Impairment (LMCI), and Mild Cognitive
cognitive Impairment (LMCI), and Mild Cognitive
etween subtle variations in brain structure during these
sing SMOTE and leverages advanced CNN layers to
strates the model's c etween subtle variations in brain structure during these
sing SMOTE and leverages advanced CNN layers to
strates the model's capability to manage the inherent
potential for improving diagnostic precision and aiding
to dete sing SMOTE and leverages advanced CNN layers to
strates the model's capability to manage the inherent
potential for improving diagnostic precision and aiding
to detect. This makes classification between disease states
part natrates the model's capability to manage the inherent
potential for improving diagnostic precision and aiding
to detect. This makes classification between disease states
particularly challenging for both clinicians and au potential for improving diagnostic precision and aiding
to detect. This makes classification between disease states
particularly challenging for both clinicians and automated
systems.
Recent advances in artificial intellig to detect. This makes classification between disease states
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Recent advances in artificial intelligence (AI) and deep
learning have shown promising results to detect. This makes classification between disease states
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Recent advances in artificial intelligence (AI) and deep
learning have shown promising results in medical image
analysis. Convolutional neural networks (C systems.
Recent advances in artificial intelligence (AI) and deer
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patt analysis. Convolutional neural networks (CNNs) have
become a popular choice for tasks such as image
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patterns in data. However, many medical datasets suffer fro become a popular choice for tasks such as image classification due to their ability to capture complex spatial patterns in data. However, many medical datasets suffer from class imbalance, as in the case of Alzheimer's dis classification due to their ability to capture complex spatial
patterns in data. However, many medical datasets suffer from
class imbalance, as in the case of Alzheimer's disease
datasets, where advanced stages of the dise

ACK 2024 학술발표대회 논문집 (31권 2호)
generalize across all stages of the disease. By leveraging
CNNs' powerful feature extraction capabilities and SMOTE's
data handling approach, our model aims to improve
classification accuracy a ACK 2024 학술발표대회 논문집 (31권 2호)
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classification accuracy a ACK 20

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generalize across all stages of the disease. By

CNNs' powerful feature extraction capabilities and

data handling approach, our model aims to

classification accuracy across five distinct

Alzheimer's di

generalize across all stages of the disease. By leveraging
CNNs' powerful feature extraction capabilities and SMOTE's
data handling approach, our model aims to improve
classification accuracy across five distinct stages of generalize across all stages of the disease. By leveraging
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data handling approach, our model aims to improve
classification accuracy across five distinct stages of generalize across all stages of the disease. By leveraging
CNNs' powerful feature extraction capabilities and SMOTE's
data handling approach, our model aims to improve
classification accuracy across five distinct stages of CNNs' powerful feature extraction capabilities and SMOTE's
data handling approach, our model aims to improve
classification accuracy across five distinct stages of
to advanced AD.
This research not only contributes to the data handling approach, our model aims to improve
classification accuracy across five distinct stages of
Alzheimer's disease, ranging from cognitively normal (CN)
to advanced AD.
This research not only contributes to the g classification accuracy across five distinct stages of
Alzheimer's disease, ranging from cognitively normal (CN)
to advanced AD.
This research not only contributes to the growing body of
work in automated AD classification management. This research not only contributes to the grow
work in automated AD classification but also hilp
potential of integrating data augmentation tech
SMOTE in healthcare applications. The model
performance in distinguishing sub For the material of integrating data augmentation but also highlights the
tential of integrating data augmentation techniques like
MOTE in healthcare applications. The model's enhanced
formance in distinguishing subtle bra potential of integrating data augmentation techniques like

SMOTE in healthcare applications. The model's enhanced

performance in distinguishing subtle brain structural

differences at various stages of AD progression sho SMOTE in healthcare applications. The model's enhanced
performance in distinguishing subtle brain structural
differences at various stages of AD progression showcases its
utility for real-world clinical diagnostics. Our st

performance in distinguishing subtle brain structural
differences at various stages of AD progression showcases its
utility for real-world clinical diagnostics. Our study aims to
provide a robust and scalable solution for differences at various stages of AD progression showcases its
utility for real-world clinical diagnostics. Our study aims to
provide a robust and scalable solution for improving early-
stage diagnosis, which is critical fo utility for real-world clinical diagnostics. Our study aims to
provide a robust and scalable solution for improving early-
stage diagnosis, which is critical for effective disease
management.
2. Related Work
Recent advance provide a robust and scalable solution for improving early-
stage diagnosis, which is critical for effective disease
management.
2. Related Work
Recent advancements in Alzheimer's disease (AD)
learning techniques to enhanc stage diagnosis, which is critical for effective disease
management.

2. Related Work

Recent advancements in Alzheimer's disease (AD)

classification increasingly utilize machine learning and deep

learning techniques to Related Work

Recent advancements in Alzheimer's disease (AD)

Recent advancements in Alzheimer's disease (AD)

reming techniques to enhance diagnostic accuracy. Early

proaches relied on traditional algorithms and hand-cr **2. Related Work**

Recent advancements in Alzheimer's disease (AD)

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Recent advancements in Alzheimer's disease (AD)

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classification increasingly utilize machine learning and deep
learning techniques to enhance diagnostic accuracy. Early
approaches relied on traditional algorithms and hand-crafted
features, but these were limited by featu Examing techniques to enhance diagnostic accuracy. Early

approaches relied on traditional algorithms and hand-crafted

features, but these were limited by feature extraction quality

and brain complexity. The rise of conv approaches relied on traditional algorithms and hand-crafted

features, but these were limited by feature extraction quality

and brain complexity. The rise of convolutional neural

networks (CNNs) has revolutionized this features, but these were limited by feature extraction quality

and brain complexity. The rise of convolutional neural

networks (CNNs) has revolutionized this field by automating

feature extraction and classification fro and brain complexity. The rise of convolutional neural

networks (CNNs) has revolutionized this field by automating

feature extraction and classification from raw imaging data.

Related works such as Arafa's deep learning networks (CNNs) has revolutionized this field by automating

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Related works such as Arafa's deep learning framework for

early diagnosis of AD on MRI images (202 research. Related works such as Arafa's deep learning framework for

rely diagnosis of AD on MRI images (2024) showcase the

lity of CNNs in analyzing MRI data, highlighting

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train early diagnosis of AD on MRI images (2024) showcase the

utility of CNNs in analyzing MRI data, highlighting

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feature extraction[1]. Similarly, Chen's graph neural net utility of CNNs in analyzing MRI data, highlighting

improvements in diagnostic accuracy through enhanced training and evaluation.

feature extraction[1]. Similarly, Chen's graph neural network techniques that ensure data improvements in diagnostic accuracy through enhanced training and evalue

feature extraction[1]. Similarly, Chen's graph neural network techniques that ensus

for functional brain network analysis, offering ereater extrac

feature extraction[1]. Similarly, Chen's graph neural network

approach (2023) introduces a learnable subdivision technique extraction and classificati

for functional brain network analysis, offering greater

interpretab approach (2023) introduces a learnable subdivision technique
for functional brain network analysis, offering greater
for functional brain network analysis, offering greater
and evaluation strategies use
studies underscore for functional brain network analysis, offering greater

interpretability in cognitive disorder diagnosis[2]. These

studies underscore the significance of deep learning

advancements and inform the methods explored in th interpretability in cognitive disorder diagnosis[2]. These performance.

studies underscore the significance of deep learning

reasured.

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Despite these improvements, class imbalance remains a Alzheim studies underscore the significance of deep learning

advancements and inform the methods explored in this

The dataset used for this

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The dataset used for this

class imbalance remains a Alzheimer's Disease Ne advancements and inform the methods explored in this 3.1. Dataset

research. The dataset used for

Clease improvements, class imbalance remains a Alzheimer's Disease Neur

challenge. AD datasets often have disproportionate research. The dataset used

Despite these improvements, class imbalance remains a

challenge. AD datasets often have disproportionate comprises a total of

representations of disease stages, leading to biased models. cate Despite these improvements, class imbalance rechallenge. AD datasets often have disproper
representations of disease stages, leading to biased
Techniques like Synthetic Minority Over-s:
Technique (SMOTE) address this by ge representations of disease stages, leadin
Techniques like Synthetic Minori
Technique (SMOTE) address this by samples for underrepresented classes[3
fairness and generalization. Integrating S
as explored in this study, prov EXERCT: This section outlines the methodology of our study,

This section of the methodology of our study, and the methodology of any synthetic sexes and generalization. Integrating SMOTE with CNNs,

The dataset's distrib For the configure (SMOTE) address this by generating synthetic $\frac{ENACI}{7,430}$ and generating SMOTE with CNNs, and generating SMOTE with CNNs a explored in this study, provides a promising solution to take class implement

performance. Figure 1. Random Sample Images from Each
training and evaluation. We begin w
techniques that ensure data uniformity and
describe the SMOTE-ADNet model archiextraction and classification. Finally, we c
and evaluation strate Figure 1. Random Sample Images from Each Alzheimer Class
ining and evaluation. We begin with preprocessing
chniques that ensure data uniformity and quality. Next, we
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Example 18 Apple 10 and the sense of this study is derived from the
sense Neuroimaging Initiative (ADNI) and
of 16,200 images. These images are
vealistinct classes, representing different
r's disease and cognitive states **1. Dataset**
 **1. The dataset used for this study is derived from the zheimer's Disease Neuroimaging Initiative (ADNI) and
**

3.1. Dataset

The dataset used for this study is derived from the

Alzheimer's Disease Neuroimaging Initiative (ADNI) and

comprises a total of 16,200 images. These images are

categorized into five distinct classes, re **3.1. Dataset**

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Alzheimer's Disease Neuroimaging Initiative (ADNI) and
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categorized into five distinct classes, representing differen Alzheimer's Disease Neuroimaging Initiative (ADNI) and
comprises a total of 16,200 images. These images are
categorized into five distinct classes, representing different
stages of Alzheimer's disease and cognitive states comprises a total of 16,200 images. These images are
categorized into five distinct classes, representing different
stages of Alzheimer's disease and cognitive states:
 $\frac{CN}{7,430}$ $\frac{240}{240}$ $\frac{72}{72}$ $\frac{922}{7,536$ categorized into five distinct classes, representing differ

stages of Alzheimer's disease and cognitive states:

CN EMCI LMCI MCI AD Tot

7,430 240 72 922 7,536 16,2

<Table 1> ADNI Dataset

The dataset's distribution sho *<Table 1> ADNI Dataset*
 The 12> ADNI Dataset
 CN classes being well-represented, while MCI,

MCI classes have fewer samples. To address

ce, the Synthetic Minority Over-sampling

SMOTE) was applied. SMOTE generates

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Post-SMOTE, the dataset was expanded to a total of and an accuracy of 99.41% on

680 images, with each class now containing 7,536 images. validation set resulted in a loss c

is balanced datas **ACK 2024 학술발표대회 논문집 (31권 2호)**

Post-SMOTE, the dataset was expanded to a total of and an accuracy of 99.41

37,680 images, with each class now containing 7,536 images. validation set resulted in a

This balanced dataset This balanced dataset improves model training by providing ACK 2024 ^o $\frac{1}{2}$ $\frac{1}{2}$ $\frac{1}{2}$ $\frac{1}{2}$ (31 $\frac{1}{2}$ $\frac{2}{3}$)

Post-SMOTE, the dataset was expanded to a total of and an accuracy of 99.41

37,680 images, with each class now containing 7,536 images. valid **ACK 2024 학술발표대회 논문집 (31권 2호)**

Post-SMOTE, the dataset was expanded to a total of and an accuracy of 99.4

37,680 images, with each class now containing 7,536 images. validation set resulted in a

This balanced dataset i ACK 2024 학술발:

Post-SMOTE, the dataset was expanded to a total c

37,680 images, with each class now containing 7,536 images.

This balanced dataset improves model training by providin

a fair representation of all classes ACK 2
 37,680 images, with each class now containing 7,5

This balanced dataset improves model training by

a fair representation of all classes, enhancing t

ability to generalize and perform effectively acro

stages of **RESICITE:** Post-SMOTE, the dataset was expanded to a total of and an accuracy of 99.41%

ACK 2024 ^a $\frac{1}{2}$ LM and an accuracy of 99.41%

AS0 images, with each class now containing 7,536 images. validation set resulte Post-SMOTE, the dataset was expanded to a total of and an accuracy of 99.41% c 37,680 images, with each class now containing 7,536 images. validation set resulted in a loss
This balanced dataset improves model training by

Post-SMOTE, the dataset was expanded to a total of and an accuracy of 37,680 images, with each class now containing 7,536 images. validation set resulted This balanced dataset improves model training by providing 98.12%. Post-SMOTE, the dataset was expanded to a total of and an accuracy of 99.41%

37,680 images, with each class now containing 7,536 images. validation set resulted in a la

This balanced dataset improves model training by p 37,680 images, with each class now containing 7,536 images. validation set resulted in This balanced dataset improves model training by providing 98.12%. These metrics a fair representation of all classes, enhancing the m This balanced dataset improves model training
a fair representation of all classes, enhancing
ability to generalize and perform effectively ac
stages of Alzheimer's disease.
3.2. Image Preprocessing
Resizing and Normaliza Fair representation of all classes, enhancing the model's and generalization ability to generalize and perform effectively across different ges of Alzheimer's disease.
 Paramer Preprocessing
 Paramer Preprocessing
 Pa and its percentively across different

and the montions and perform effectively across different

stages of Alzheimer's disease.
 a.g. Image Preprocessing

Resizing and Normalization is crucial for compatibility

with th stages of Alzheimer's disease.

3.2. Image Preprocessing

Resizing and Normalization: To ensure uniformity across

the input data, images are resized to a fixed dimension of 224
 \times 224 pixels. This standardization is cru **Example Preprocessing**
 Resizing and Normalization: To ensure uniformity across

the input data, images are resized to a fixed dimension of 224
 \times 224 pixels. This standardization is crucial for compatibility

with the input data, images are resized to a fixed dimen
 \times 224 pixels. This standardization is crucial for co

with the convolutional neural network (CNN) m

requires a consistent input size. Pixel values are

to a [0,1].

shifts. 224 pixels. This standardization is crucial for compatibility

224 pixels. This standardization is crucial for compatibility

th the convolutional neural network (CNN) model, which

a [0,1].
 Data Augmentation Techniques

with the convolutional neural network (CNN) model, which
requires a consistent input size. Pixel values are normalized
to a [0,1].
Data Augmentation Techniques: To mitigate overfitting
data augmentation techniques are e Frame the conventional ideal increases the case, which

requires a consistent input size. Pixel values are normalized

to a [0,1].
 Data Augmentation Techniques: To mitigate overfitting

and enhance the model's generali Equivale and the model of the architecture

Let \overline{L} and \overline{L} and enhance the model's generalization capability, various

data augmentation techniques: To mitigate overfitting Figure 2. Train and

data augmentatio **Example 1.** The **Data Augmentation Techniques:** To mitigate overfitting Figure 2. Train

and enhance the model's generalization capability, various

data augmentation techniques are employed. These include

subtre and th accuracy. de and comprises several and contributed comprises several key components:
 and Convolutional Convolution Convolution in the model is specifically designed to formula:
 3.3. Model Architecture The SMOTE-ADNet model is **Example 19 Example 19 3.3. Model Architecture**

The SMOTE-ADNet model is specifically designed to

extract relevant features from brain scan images and classify

them into five Alzheimer's disease stages: AD, CN, EMCI, where x_{base} is the ori The SMOTE-ADNet model is specifically designed to

extract relevant features from brain scan images and classify

then into five Alzeleimer's discass etages: AD, CN, EMCI, and MCI. The architecture emphasizes capturing *n* **EXECT:** The motion of the motion of the architecture extracted by the convolutional layers. These layers apply the extraction and α are accuracy.
 EXECT: EXECT: EXECT: EXECT: EXECT: EXECT: EXECT: EXECT:

• Convolutional Layers (Conv2D): These layers apply

filters to detect local features within the input images.

• Max Pooling Layers (MaxPool2D): Max pooling reduces

the spatial dimensions of the feature maps by selecting Filters to detect local reatures within the input images.

• Max Pooling Layers (MaxPool2D): Max pooling reduces

the spatial dimensions of the feature maps by selecting the

maximum value within a defined window.

• Dense • Max Pooling Layers (MaxPool2D): Max pooling reduces

the spatial dimensions of the feature maps by selecting the

maximum value within a defined window.

• Dense Layers: Fully connected layers aggregate the

features ex the spatial dimensions of the feature maps by selecting the

maximum value within a defined window. The
 • Dense Layers: Fully connected layers aggregate the

features extracted by the convolutional layers.

• **Dropout L • Dense Layers:** Fully connected layers aggregate features extracted by the convolutional layers.

• Dropout Layers: Dropout is used to prevent overfittin randomly setting a fraction p of the neurons to zero du each train Traning: The proposed model is trained using the training

here all the model of the increase states. The
 Transition Functions and Output Layer: The ReLU directions of the model is training iteration.

Activation Funct

• Dropout Layers: Dropout is used to prevent overfitting by

• Dropout Layers: Dropout is used to prevent overfitting by

each training iteration.

• Activation Functions and Output Layer: The ReLU

(Rectified Linear Unit **EXECUTE:**
 EXECUTE: The ReLU of the neurons of the neurons to zero during
 EXECUTE: The ReLU of the counts of true position
 Activation Functions and Output Layer: The ReLU the counts of true position

(Rectified L Example the model intention of the validation and **C** external training iteration.
 Example training iteration Eurotions and Output Layer: The ReLU (Rectified Linear Unit) activation function is applied in the categor The model utilizes a batch size of 32, and the number of Frience is the model unitary and beyond the model active of the model differentiates between

(Rectified Linear Unit) activation function is applied in the underly the model differentiates between

the softmax function is (vection and the model differentiates between

intended and the softmax function is employed to produce a probability

the softmax function is employed to produce a probability

distribution over the five target classes.
 and the softmax function is employed to produce a probability
distribution over the five target classes.
3.4. Training and Evaluation expresses a represent the proposed model is trained using the Adam
optimizer with cat Complementing the contribution over the five target classes.
 Examplementing the controlling: The proposed model is trained using the Adam

timizer with categorical cross-entropy loss. The training

timizer with categor

 $\frac{1220}{1220}$
and an accuracy of 99.41% on the training set, while the
validation set resulted in a loss of 0.0969 and an accuracy of
98.12%. These metrics indicate a high level of performance
and generalization ability i $\pm \pm \frac{1}{2}$ (31 \pm 2 \pm)
and an accuracy of 99.41% on the training set, while the
validation set resulted in a loss of 0.0969 and an accuracy of
98.12%. These metrics indicate a high level of performance
and gener 98.12%. These metrics indicate a high level of performance and generalization ability.

These metrics indicate a high level of performance and generalization ability.

These severalization ability. $\frac{d \pm \pm 2 \times 3 \times 2 \times 2}{d \pm 2 \times 2 \times 2}$

and an accuracy of 99.41% on the training set, while

validation set resulted in a loss of 0.0969 and an accurac

98.12%. These metrics indicate a high level of performand

and gen

Figure 2. Train and Validation Loss & Accuracy

The dataset is divided into training and testing sets with an

80-20 split. To address class imbalance, the Synthetic

Minority Over-sampling Technique (SMOTE) is applied,
 Figure 2. Train and Validation Loss & Accuracy

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The dataset is divided into training and testing sets with an

80-20 split. To address class imbalance, the Synthetic

Minori formula: Figure 2. Train and Validation Loss & Accuracy
taset is divided into training and testing sets with an
lit. To address class imbalance, the Synthetic
Over-sampling Technique (SMOTE) is applied,
nerates synthetic samples f Figure 2. Train and Validation Loss & Accuracy
 The dataset is divided into training and testing sets with an

80-20 split. To address class imbalance, the Synthetic

Minority Over-sampling Technique (SMOTE) is applied, Figure 2. Train and Validation Loss & Accuracy

The dataset is divided into training and testing sets with an

80-20 split. To address class imbalance, the Synthetic

Minority Over-sampling Technique (SMOTE) is applied,
 Figure 2. Fram and valuation Loss & Accuracy
The dataset is divided into training and testing sets with an
-20 split. To address class imbalance, the Synthetic
inority Over-sampling Technique (SMOTE) is applied,
sich gene The dataset is divided into training and testing sets with an 80-20 split. To address class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) is applied, which generates synthetic samples for minority clas The dataset is divided the during and testing sets θ and θ and θ and θ and θ and θ of θ and θ and θ and θ **Accuracy** measures and the model's predictions. Accuracy provides a general relation of the model of the model and $x_{new} = x_{base} + \lambda(x_{neighbor} - x_{base})$ (3) are x_{base} is the original sample, $x_{neighbor}$ is a selected nearest ighbor, and

$$
x_{new} = x_{base} + \lambda (x_{neighbor} - x_{base}) \quad (3)
$$

predictions. The sumpring is completed to the provider sumplest to the SMOTE algorithm creates new samples using the following formula:
 $x_{new} = x_{base} + \lambda(x_{neighbor} - x_{base})$ (3)

where x_{base} is the original sample, $x_{neighbor}$ is a select SMOTE algorithm creates new samples using the following

formula:
 $x_{new} = x_{base} + \lambda(x_{neighbor} - x_{base})$ (3)

where x_{base} is the original sample, $x_{neighbor}$ is a selected nearest

neighbor, and λ is a random number between 0 and 1.
 E formula:
 $x_{new} = x_{base} + \lambda(x_{neighbor} - x_{base})$

where x_{base} is the original sample, $x_{neighbor}$ is a se

neighbor, and λ is a random number between 0 and 1
 Evaluation: The performance of the model

using several key metrics to ensur

subtle differences in brain structures to enhance classification

The model comprises several key components:
 • Convolutional Layers (Conv2D): These layers apply
 • Convolutional Layers (Conv2D): These layers apply
 decuracy.
 •• Convolutional Layers (Conv2D): These layers apply

•• **Convolutional Layers (Conv2D):** These layers apply

•• **Ax Pooling Layers (MaxPool2D):** Max pooling reduces

•• **Max Pooling Layers (MaxPool2D):** Ma $x_{new} = x_{base} + \lambda(x_{neighbor} - x_{base})$ (3)
 x_{new} = x_{base} *is the original sample,* $x_{neighbor}$ *is a selected nearest*
 ighbor, and λ *is a random number between 0 and 1.*
 Evaluation: The performance of the model is assessed

in *Thew Phase I* N Chelghbor *Phase C*)
where x_{base} is the original sample, $x_{neighbor}$ is a selected nearest
neighbor, and λ is a random number between 0 and 1.
Evaluation: The performance of the model is assessed
us metre x_{base} is the original study. $x_{neighbor}$ is a selected nearest neighbor, and λ is a random number between 0 and 1.
 Evaluation: The performance of the model is assessed using several key metrics to ensure a compreh detailed breakdown of the model's performance across the model is assessed using several key metrics to ensure a comprehensive evaluation of its efficacy.
 Accuracy measures the overall correctness of the model's predict **Evaluation:** The performance of the model is assessed
using several key metrics to ensure a comprehensive
evaluation of its efficacy.
Accuracy measures the overall correctness of the model's
predictions. Accuracy provid using several key metrics to ensure a comprehensive
evaluation of its efficacy.
Accuracy measures the overall correctness of the model's
predictions. Accuracy provides a general measure of how
often the model's predictio evaluation of its efficacy.
 Accuracy measures the overall correctness of the model's

predictions. Accuracy provides a general measure of how

often the model's predictions match the true labels, reflecting

its overall Accuracy measures the overall correctness of the model's
predictions. Accuracy provides a general measure of how
often the model's predictions match the true labels, reflecting
its overall reliability.
The evaluation metri predictions. Accuracy provides a general measure of
often the model's predictions match the true labels, reflect
its overall reliability.
The evaluation metrics used in this study provid
thorough assessment of the model's ten the model's predictions match the true labels, reflecting
overall reliability.
The evaluation metrics used in this study provide a
prough assessment of the model's ability to classify
zheimer's disease states. The con its overall reliability.

The evaluation metrics used in this study provide a

thorough assessment of the model's ability to classify

Alzheimer's disease states. The confusion matrix offers a

detailed breakdown of the m The evaluation metrics used in this study provide a
thorough assessment of the model's ability to classify
Alzheimer's disease states. The confusion matrix offers a
detailed breakdown of the model's performance across the

The counts of true positives and raise positives for each category. This matrix is essential for understanding how well the model differentiates between the classes and identifying areas for potential improvement. Complementing the confusion matrix, the classification report includes precision, recall, and F1-score metrics for each class are defined as follows:\n\n
$$
\begin{cases}\n\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \\
\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \\
\text{F1} - \text{Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}\n\end{cases}
$$
\nwhere:\n\n*TP denotes True Positives, the number of correctly predicted positives instances.*\n*FP denotes False Positives, the number of incorrectly predicted positives instances.*\n\nD).

where:

instances.

EVALUAT SET ANTIFY ARE SET ANCHOLOGET ARE RELIGIONS As the relations of the model's predicted use and the model performs are religions are religions are religions with high accuracy and balanced effectiveness across al capability to identify relevant instances. The F1-scores E
 $\frac{1}{2}$ and a one of the model of As evaluated Label wice

Frequenced Label wice

Figure 3. Normalized Confusion Matrix

These metrics collectively confirm that the model performs

with high accuracy and balanced effectiveness across all

exact and the mo abilityof Predicted Label

Predicted Label

Figure 3. Normalized Confusion Matrix

These metrics collectively confirm that the model performs

with high accuracy and balanced effectiveness across all

categories. Precisi Figure 3. Normalized Confusion Matrix Figure 3. Normalized Confusion Matrix *AD* 0.97

These metrics collectively confirm that the model performs

with high accuracy and balanced effectiveness across all

predictions are Figure 3. Normalized Confusion Matrix
These metrics collectively confirm that the model perfor
with high accuracy and balanced effectiveness across
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predictions These metrics collectively confirm that
with high accuracy and balanced effe
categories. Precision values indicate that
predictions are reliable, while recall va
capability to identify relevant instant
further highlight th th high accuracy and balanced effectiveness across all $\frac{LMCI}{MCI}$ 1.00 1

tegories. Precision values indicate that the model's positive

delictions are reliable, while recall values demonstrate its

pability to identify categories. Precision values indicate that the model's positive

predictions are reliable, while recall values demonstrate its

capability to identify relevant instances. The F1-scores

further highlight the model's balanc predictions are reliable, while recall values demonstrate its

capability to identify relevant instances. The F1-scores

further highlight the model's balanced performance. Overall,

these evaluation tools underscore the m capability to identify relevant instances. The F1-scores macro avg 0.

further highlight the model's balanced performance. Overall, $\frac{mearo\,avg}{weghted\,avg}$ 0.

these evaluation tools underscore the model's robustness, its

ab further highlight the model's balanced performance. Overall
these evaluation tools underscore the model's robustness, its
ability to handle class imbalance effectively, and its capacity
to deliver accurate predictions cruc

Examplethe model's robustness, its

ility to handle class imbalance effectively, and its capacity

deliver accurate predictions crucial for classifying

Zheimer's disease stages.
 Results
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ability to handle class imbalance effectively, and its capacity

to deliver accurate predictions crucial for classifying

Alzheimer's disease stages.

4. Results

The SMOTE-ADNet model achieved impressive results in [2] Do to deliver accurate predictions crucial for classifying

Alzheimer's disease stages.
 4. Results
 4. Resul Alzheimer's disease stages. [1] Doaa Ahmed Arafa etc. "

early diagnosis of Alzheir

Multimedia Tools and App

The SMOTE-ADNet model achieved impressive results in [2] Dongdong Chen etc. "

dassifying Alzheimer's disease 4. Results

The SMOTE-ADNet model achieved impressive results in [2] Dongdong Chen etc. "I

classifying Alzheimer's disease states, as evidenced by both Neural Network for Funct

the test loss and accuracy metrics. The mod **4. Kesuts**

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The SMOTE-ADNet model achieved impressive results in [2] Dongdong Chen etc.

classifying Alzheimer's disease states, as evidenced by both Neural Network for Fun

the test loss and ac The SMOTE-ADNet model achieved impressive results in [2] Dongdong Chen etclassifying Alzheimer's disease states, as evidenced by both Neural Network for F
the test loss and accuracy metrics. The model recorded a test and classifying Alzheimer's disease states, as evidenced by both
the test loss and accuracy metrics. The model recorded a test
and Interpretable Cognit
its high relability and effectiveness.
The detailed evaluation further hi the test loss and accuracy metrics. The model recorded a test and Interpretable Cogr

loss of 0.0826 and a test accuracy of 0.9823, demonstrating MICCAI Canada 2023, pp

its high reliability and effectiveness.

The detaile loss of 0.0826 and a test accuracy of 0.9823, demonstrating MICCAI Canada 2023, pp 56

its high reliability and effectiveness. [3] Blagus, Rok, Lusa, Lara "SM

The detailed evaluation further highlights the model's

perfor its high reliability and effectiveness.

The detailed evaluation further highlights the model's

performance. The classification report reveals consistently

high precision, recall, and F1-scores across all classes.

PP The detailed evaluation further highlights
performance. The classification report reveals
high precision, recall, and F1-scores across
Specifically, precision values range from 0.97 f
for LMCI, while recall values span fro ¹
high precision, recall, and F1-scores
Specifically, precision values range from
for LMCI, while recall values span from
for EMCI and LMCI. The F1-scores
performance, ranging from 0.97 to 1.0
stands at 98%, reflecting t pecifically, precision values range from 0.97 for AD to 1.00 a CKNOW

or LMCI, while recall values span from 0.95 for CN to 1.00 This work was supported in

or EMCI and LMCI. The F1-scores also show strong (50%) and the Ko for LMCI, while recall values span from 0.95 for CN to 1.00 This work was support
for EMCI and LMCI. The F1-scores also show strong (50%) and the Korea g
performance, ranging from 0.97 to 1.00. Overall accuracy the ICT Cre

 $\frac{d \pm \pm \Delta}{d \pm 2}$
disease states with notable precision and reliability. The
model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 for EMCI a 1 \pm \pm (31 \pm 2 \pm)
disease states with notable precision and reliability. The
model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for disease states with notable precision and reliability. The
model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 for EMCI and LMCI. These metric i $\pm \pm \pm \Delta$ (31 ± 2 ± i)
disease states with notable precision and reliability. The
model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 for E stages of Alzheimer's disease states with notable precision and reliability. The
model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 for EMCI disease states with notable precision and reliability. The
model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 for EMCI and LMCI. These metric d $\pm \pm \pm \Delta$ (31 $\pm 2\pm \Delta$)
disease states with notable precision and reliability. The
model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 fo $\frac{12.62}{12.61}$
disease states with notable precision and reliability. The
model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 for EMCI and sease states with notable precision and reliability. The
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om 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
V and 1.00 for EMCI and LMCI. These metrics refl disease states with notable precision and reliability. The
model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 for EMCI and LMCI. These metric disease states with notable precision and reliability. The
model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 for EMCI and LMCI. These metric model excels across all five classes, with precision ranging
from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for
CN and 1.00 for EMCI and LMCI. These metrics reflect a
robust ability to accurately differentiate betw

from 0.97 for AD to 1.00 for LMCI, and recalls of 0.95 for CN and 1.00 for EMCI and LMCI. These metrics reflect a robust ability to accurately differentiate between the various stages of Alzheimer's disease. The high F1-sc CN and 1.00 for EMCI and LMCI. These metrics reflect a
robust ability to accurately differentiate between the various
stages of Alzheimer's disease. The high F1-scores and an
overall accuracy of 0.98 further confirm the mo robust ability to accurately differentiate between the various
stages of Alzheimer's disease. The high F1-scores and an
overall accuracy of 0.98 further confirm the model's
effectiveness, illustrating its capability to ha stages of Alzheimer's disease. The high F1-scores and an
overall accuracy of 0.98 further confirm the model's
effectiveness, illustrating its capability to handle both class
imbalance and precise classification.
The promi overall accuracy of 0.98 further confirm the
effectiveness, illustrating its capability to handle
imbalance and precise classification.
The promising results underscore the potential of
ADNet as a significant advancement

aiming to contribute valuable insights to the field and support				
ongoing efforts in the early detection and classification of				
Alzheimer's disease.				
	precision	recall	f1-score	support
AD	0.97	0.96	0.96	1,131
CN	0.97	0.96	0.97	1,130
EMCI	0.99	1.00	0.99	1,130
LMCI	1.00	1.00	1.00	1,131
МCI	0.98	0.99	0.98	1,130
accuracy			0.98	5,652
macro avg	0.98	0.98	0.98	5,652
weighted avg	0.98	0.98	0.98	5,652
	<table 3=""> ADNI Classification Report</table>			
		References		
[1] Doaa Ahmed Arafa etc. "A deep learning framework for				
	early diagnosis of Alzheimer's disease on MRI images"			
	Multimedia Tools and Applications, 83(2), 3767--3799			
[2] Dongdong Chen etc. "Learnable Subdivision Graph				
	Neural Network for Functional Brain Network Analysis			
and	Interpretable Cognitive Disorder Diagnosis"			
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[3] Blagus Rok Lusa Lara "SMOTE for high-dimensional				

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early diagnosis of Alzheimer's disease on MRI images weighted avg $\left|$ 0.98 0.98 0.98 5.652
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[1] Doaa Ahmed Arafa etc. "A deep learning framework for early diagnosis of Alzheimer's disease on MRI images"

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