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 Brain Tumor Identification on Mall images using deep
 Learning techniques

Zheshu Jia Date of publication xxx. 00, 0000, date of current version xxx. 00, 0000.

Divisiod Object Identification of MRI images using deep

Classification of MRI images using deep

learning techniques

Zheshu Jia, Deyun Chen⁺
Ch **Brain Tumor Identification and

Classification of MRI images using deep

learning techniques**
 **Zheshu Jia, Deyun Chen^{*}

School of Computer Science and Technology, Harbin University of Science and Technology, Harbin 150**

China chen_deyun@126.com **Abstract**

Classification of MRI images using deep
 Classification of MRI images using deep
 Learning techniques

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China

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 Learning techniques
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Abstract

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action, segmentation, an Zheshu Jia, Deyun Chen^{*}

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 Abstract

The detection, segmentation, and extraction from Mag Zheshu Jia, Deyun Chen⁺
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The detection, segmentation, and extraction from Magnetic Resonance I China

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Abstract

The detection, segmentation, and extraction from Magnetic Resonance Imaging (MRI) images of

contaminated tumor areas are significant concerns; however, a repetitive and extensive task chen destricts are set as a significant concerns, however, a repetitive and extensive task executed by contaminated tumor areas are significant concerns; however, a repetitive and extensive task executed by radiologists or Abstract

The detection, segmentation, and extraction from Magnetic Resonance Imaging (MRI) images of

contaminated tumor areas are significant concerns; however, a repetitive and extensive task executed by

aradiologists The detection, segmentation, and extraction from Magnetic Resonance Imaging (MRI) images of contaminated tumor areas are significant concerns; however, a repetitive and extensive task executed by randiologists or clinical In execution, exgeneration, and extraction from Magnetic resonance from prediction, and extraction from the containinated tumor rareas are significant concerns; however, a repetitive and extensive tak executed by radiologi contaminated tumor areas are significant concerns; nowever,
radiologists or clinical experts relies on their expertise. Image
anatomical structure of the human organ. Detection of human
techniques is challenging. In this p anatomical structure of the human organ. Detection of human brain sharehoniques is challenging. In this paper, a Fully Automatic Heterogeneous Segmentation based on deep learning Vector Machine (FAHS-SVM) has been proposed niques. The present work proposes the separation of the whole cerebral venous systing with the addition of a new, fully automatic algorithm based on structural, morp

2. The segmenting function is distinguished by a high l with the addition of a new, fully automat
try details. The segmenting function is d
and the neighboring brain tissue. ELM is a
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RI images, the probabilistic neural network
the accu relaxometry details. The segmenting function is distinguished by a high level of uniformial anatomy and the neighboring brain tissue. ELM is a type of learning algorithm consisting of comes a brain and comes Social network anatomy and the neighboring brain tissue. ELM is a type of learning algorithm consisting of one of biden nodes. Such networks are used in various areas, including regression and classification brain checking the accuracy o layers of hidden nodes. Such networks are used in various areas, including regression and class
brain MRI images, the probabilistic neural network classification system has been utilized for
checking the accuracy of tunor segmentation based on deep learning
le cerebral venous system into MRI
ead on structural, morphological, and
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 le cerebral venous system into MRI
sed on structural, morphological, and
a high level of uniformity between
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uding regression and classification. In
stem has been utilized for training

Meningioma and Gliomas are low-grade cancer known as shows the 2D model of brain tumor detection, and 1(b) showing benign tumors and high-grade tumors classified as malignant the MRI image of a brain tumor tumors, includin brain MRI images, the probabilistic neural network classification system has been utilized fc
checking the accuracy of tumor detection in images. The numerical results show almost 98.5
in detecting abnormal and normal tiss checking the accuracy of tumor detection in images. The numerical results show almost 98.51% achieved in detecting abormal and normal tissue from brain Magnetic Resonance images that demonstrefficiency of the system sugges in detecting abnormal and normal tissue from brain Magnetic Resonance images that
efficiency of the system suggested.
Keywords: Brain Tumor Detection, Classification, Segmentation, Deep learning, ELM
1. The **Importance a** efficiency of the system suggested.
 Keywords: Brain Tumor Detection, Classification, Segmentation, Deep learning, ELM

1. The **Importance and Significance of Detecting** blood vessels and the d
 Brain Tumors or less th **Keywords: Brain Tumor Detection, Classification, Segmentation, Deep learning, ELM**

1. The **Importance and Significance of Detecting** blood vessels and the developme

Brain Tumors or less the tumor [9].

In clinical studi **Keywords: Brain Tumor Detection, Classification, Segmentation, Deep learning, ELM**

1. The **Importance and Significance of Detecting** blood vessels and the developm
 Example 1.1 The high resolution, contrast, and clear 1. The Importance and Significance of Detecting

Brain Tumors

or less the tumor [9].

In clinical studies on brain anatomy, MRI has become a crucial

tool [1]. The high resolution, contrast, and clear separation of

segme 1. The importance and Significance of Detecting

blood vessels and the devel

In clinical studies on brain anatomy, MRI has become a crucial incomer reatment plans

tool [1]. The high resolution, contrast, and clear separa **Exam Tumors** or less the tumor provides and tool [1]. The high resolution, contrast, and clear separation of segment the pathological and the soft issue enable doctors to identify specific diseass with their sub-regions [In clinical studies on brain anatomy, MRI has become a crucial

tool [1]. The high resolution, contrast, and clear separation of

segment the pathological and

the soft tissue enable doctors to identify specific diseases
 m cmea sutteras on form antalony, with also escone a crucial in cancer teament pans are considered brain in colored and the soft tissue enable doctors to identify specific diseases with their sub-regions [10]. The accurate tool [1]. The fign resolution, contrast, and clear separation of segment the pathological
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evolutionary trends, for preparation, the best the sort ussue enable doctors to lentury spectic diseases
accurately [2]. For understanding pathology, for assessing a crucial task for all
evolutionary trends, for preparation, the best surgical method or which consists o actuately [2]. To trenessianing panology, for assessing
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and healthy tissues that comprise the Magnetic Resonance
and healthy tissues that comprise the Magnet evolutionary treneas, for preparation, the best surgical memoi or whence one when consists of emmating
alternatives possible, an exact segmentation of the pathological [11]. [12] This operation is too
and healthy tissues t anternatives possible, an exact segmentation of the partiological (11.1. [1.2] Ins operation
and healthy tissues that comprise the Magnetic Resonance challenging, given the
image are necessary [3]. Automated segmentation m ma neuatury ussues that comprise the variance chance chance chance are immediated in the mange are necessary [3]. Automated segmentation methods are a image provides [13]. In gene helpful solution to help management with u mage are necessary [15]. Naturanted segmentation methods are a mage provotes [113]. In general subtrination to trace the boundaries of various tissue areas, and concurrently [14]. Standard by allowing automated volumetric melpul solution to neip management with untentable degrees or images, the radiologist conductive of pathologic MRI signal protocols provide a high-reandysis [4]. The tumor represents uncontrolled cancer cell space [15]. It automation to trace the boundaries of various usine areas, and concurrently [14]. Sambard the abigh-resol sprovide a high-resol sprovide a high-resol analysis [4]. The tumor represents uncontrolled cancer cell space [15].

a high level of uniformity between

g algorithm consisting of one or more

uding regression and classification. In

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sonance images that demonstr g algorithm consisting of one or more
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results show almost 98.51% accuracy

sonance images that demonstrate the

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blood vessels and the development of necrosis (dead cells) more

or less the tumor [9 results show almost 98.51% accuracy

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blood vessels and the development of necrosis (dead cells) more

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In cancer treatment plans and cancer res sonance images that demonstrate the
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In cancer treatment plans and cancer research, it is essential to
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with thei blood vessels and the development of necrosis (dead cells) more
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In cancer treatment plans and cancer research, it is essential to
segment the pathological and healthy brain tissues from MRI
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In cancer treatment plans and cancer research, it is essential to
segment the pathological and healthy brain tissues from MRI
with their sub-regions [10]. The segmentation of images remains
a crucial In cancer treatment plans and cancer research, it is essential to
segment the pathological and healthy brain tissues from MRI
with their sub-regions [10]. The segmentation of images remains
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segment the pathological and healthy brain tissues from MRI
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with their sub-regions [10]. The segmentation of images remains
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which consists of eliminating regions with their sub-regions [10]. The segmentation of images remains
a crucial task for all medical image processing techniques,
which consists of eliminating regions of interest from images
[11]. [12] This operation is too lon a cructal task for all medical mage processing techniques, which consists of eliminating regions of interest from images [11]. [12] This operation is too long, tedious, and in some cases, challenging, given the immense amo Which consists of eliminating regions of interest from images

[11]. [12] This operation is too long, tedious, and in some cases,

challenging, given the immense amounts of data that every

image provides [13]. In general, [11]. [12] This operation is too long, teations, and in some cases
challenging, given the immense amounts of data that every
image provides [13]. In general, when segmenting brain tumon
images, the radiologist considers a

IEEE ACCESS' xxxxx: Brain Tumor Identification and Classification of MRI images using deep learning techniques (XXXXX)
extraction, picture representation, characterization, and essential

Figure 1: (a) 2D Model of Brain Tumor Detection (b) MRI image of a brain tumor [18] Infrared Imagging Sensor has images entired in a mention of the level of usefully control the level of usefully control the level of usefu Figure 1: (a) 2D Model of Brain Tumor Detection (b) MRI image of a brain tumor [18] medical specialist to screen

Figure 1: (a) 2D Model of Brain Tumor Detection (b) MRI image of a brain tumor [18] and detection. First of Figure 1: (a) 2D Model of Brain Tumor Detection (b) MRI image of a brain tumor [18] if elderly patients in removement (a) 2D Model of Brain Tumor Detection (b) MRI image of a brain tumor [18] Ali ARI et al. [25] intramingi Infrared Imaging Sensor that transformant at medical specialist to screen the set of utility control the level of utility control the level of utility control the level of utility of the set of the set of Brain Tumor Detec registered it (a) 20 Medical specialist to screen

Figure 1: (a) 20 Model of Brain Tumor Detection (b) MRI image of a brain tumor [18]

This work focuses on the automated segmentation of local receptive fields (ELM-

menin I(a) 1(b)

Eigure 1: (a) 2D Model of Brain Tumor Detection (b) MRI image of a brain tumor [18] Ali ARI et al. [25] introduction This work focuses on the automated segmentation of local receptive fields (ELM-

meningioma fr Figure 1: (a) 1(b) if elderly patients in remote

Figure 1: (a) 2D Model of Brain Tumor Detection (b) MRI image of a brain tumor [18] Ali ARI et al. [25] introd

This work focuses on the automated segmentation of

local re Eigure 1: (a) 2D Model of Brain Tumor Detection (b) MRI image of a brain tumor [18] Ali ARI et al. [25] introduced

Incomeningion from MR imaging in multi-spectral brain datasets.

One of the few benign tumors determined Figure 1: (a) 2D Model of Brain Tumor Detection (b) MRI image of a brain tumor [18] Ali ARI et al. [25] introd

This work focuses on the automated segmentation of local receptive fields (ELM

meningioma from MR imaging in This work focuses on the automated segmentation of local receptive fields (ELM-I
meningioma from MR imaging in multi-spectral brain datasets.

One of the few benign tumors determined in the brain region is

an meningioma Ims work locuses on the automiated segmentation of

meningional from MR imaging in multi-spectral brani datasets.

One of the few benign in multi-spectral brani region is

a meningiona [19]. Accurate tumor identification l meningioma from MK imaging in multi-spectral brain datasets.
One of the few benign tumors determined in the brain region is
a meningioma [19]. Accurate tumor identification leads to the
development of surgical indications a meningioma [19]. Accurate tumor identification leads to the

development of surgical indications in elerly persons who are

carrying intracranial meningioma [20]. In recent years, Support

Vector Machine (SVM) methods in Segmentation using a range of neurological condition aimed a
tachine (SVM) methods in MRI segmentation ianed
ateracted excellent performance [21]. Segmentation is used
tentification of contaminated tumor tissues from modes mining a range of neurological conditions have

interaction and the dentification of contaminated tumor tissues from modes

in the identification of contaminated tumor tissues from modes

in the recent literature studies.

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The significant contribution of this paper is:

SVM) for image analy

Brain Tumor identication

Segmentation using Support Vector Machine (FAHS-

Segmentation using Support Vector Machine (FAHS-

To design an Extreme learn The significant contribution of this paper is:

Segmentation using Support Vector Machine (FAHS

Segmentation using Support Vector Machine (FAHS

SVM) for brain tumor detection and segmentation.

To design an Extreme learn To propose Fully Automated Heterogeneous explored histogram-
Segmentation using Support Vector Machine (FAHS-
SVM) for brain tumor detection and segmentation.
To design an Extreme learning machine algorithm for
the experim Factor Propose Tully Automated Heterogeneous Segmentation using Support Vector Machine (FAHS

Segmentation using Support Vector Machine (FAHS

To design an Extreme learning machine algorithm for

the chassification and fea Segmentation using Support vector Machine (FAHS-

SYM) for brain tumor detection and segmentation.

To design an Extreme learning machine algorithm for

the experimental results in the

different performance variables

The **Example 12**
 Concludes the research article.
 Concludes the classification and feature extraction of MRI image.

The experimental results show high accuracy detecting brain tumors with the help of datasets.

The remai • The experimental results show high accuracy in the proton and the effecting brain tumors with the help of datasets. The remainder of the paper discussed as follows: Section 1 and background review. In section 3, a Fully The remainder of the paper discussed as follows: Section 1 and

Section 2 discussed the importance of detecting brain tumor and

Dason J. Corso et

Dason J. Corso et

Heterogeneous Segmentation using Support Vector Machine The remainder of the paper discussed as follows: Section 1 and

Section 2 discussed the importance of detecting brain tumor and background review. In section 3, a Fully Automated

Heterogeneous Segmentation using Support V

Paper

based Back propagation neural network (MLBPNN) method for
brain tumor classification systems. Besides, the system can help
doctors utilizing order and package calculations to sean the approach bends the essential section o Heterogeneous Segmentation using Support Vector Machine

(FAHS-SVM) has been proposed for brain tumor segmentation . A new

based on deep learning techniques. In section 4, the affinity-based, bototon-up, an

experimental (FAHS-SVM) has been proposed for brain tumor segmentation
based on deep learning techniques. In section 4, the
experimental results have been demonstrated. Finally, section 5
integrating soft model tasks in the concludes t based on deep learning techniques. In section 4, the experimental results have been demonstrated. Finally, section 5

experimental results have been demonstrated. Finally, section 5

2. **Background Review and Features of**

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nages using deep learning techniques (XXXXX)

extraction, picture representation, characterization, and essential
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nages using deep learning techniques (XXXXX)

extraction, picture representation, characterization, and essential
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imaging technology in this study. Instead, when the enti hages using deep learning techniques (XXXXX)
extraction, picture representation, characterization, and essential
management. MLBPNN is analyzed using infrared sensor
imaging technology in this study. Instead, when the enti extraction, picture representation, characterization, and essential
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imaging technology in this study. Instead, when the entire
structure is degraded in some subsystems, extraction, picture representation, characterization, and essential
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imaging technology in this study. Instead, when the entire
structure is degraded in some subsystems, management. MLBPNN is analyzed using infrared sensor
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structure is degraded in some subsystems, the multidimensional
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maging technology in this study. Instead, when the entire
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Infrared Imaging Sensor hat transfers t machine existence of distinguishing neural proof unbelievably
decreases. This image sensor is integrated via a Wireless
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Infrared Imaging Sensor that transfers the warm tumor data to a
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usefully control the level of ultrasoun Infrared Imaging Sensor that transfers the warm tumor data to a
medical specialist to screen the well-being situation and to
usefully control the level of ultrasound measurement, especially
if elderly patients in remote ar medical specialist to screen the well-being situation and to
usefully control the level of ultrasound measurement, especially
if elderly patients in remote areas are present.
Ali ARI et al. [25] introduced the Extreme lear usefully control the level of ultrasound measurement, especially
if elderly patients in remote areas are present.
Ali ARI et al. [25] introduced the Extreme learning machine
local receptive fields (ELM-LRF) for brain tumor if elderly patients in remote areas are present.
Ali ARI et al. [25] introduced the Extreme learning machine
local receptive fields (ELM-LRF) for brain tumor classification
and detection. First of all, non-local means and Ali ARI et al. [25] introduced the Extreme learning machine
local receptive fields (ELM-LRF) for brain tumor classification
and detection. First of all, non-local means and methods of local
smoothing have been utilized to All AKI et al. [25] introduced the Extreme learning mac
local receptive fields (ELM-LRF) for brain tumor classifice
and detection. First of all, non-local means and methods of l
smoothing have been utilized to neglect nois and detection. First of all, non-local means and methods of local
smoothing have been utilized to neglect noises. In the second
strep, the use of ELM-LRF identified cranial magnetic resonance
(MR) images as malignant or be smoothing have been utilized to neglect noises. In the second
step, the use of ELM-LRF identified cranial magnetic resonance
(MR) images as malignant or benign. The tumors were
segmented in the third phase. The purpose of step, the use of ELM-LRF identified cranal magnetic resonance (MR) images as malignant or benign. The tumors were
segmented in the third phase. The purpose of this study was
only to use cranial MR images that have mass. Th (MR) images as malignant or benign. The tumors were
segmented in the third phase. The purpose of this study was
colly to use cranial MR images that have mass. The
classification exactness of cranial MR images is 96.2 % in

The interaction of contaminated tumor tissues from modes

sary and essential; it is a procedure of dividing an image

sary and essential; it is a procedure of dividing an image

various blocks or regions which share common Manuscriptical is a procedure of dividing an image

ious blocks or regions which share common and

characteristics like gray level, texture, color, contrast,

Silesh Bhaskarres, and brightness [23].

Wavelet Transformation dentical characteristics like gray level, texture, color, contrast,

boundaries, and brightness [23].

The significant contribution of this paper is:

The remainder of the paper is:

The propose Fully Automated Heterogeneo Section 2 discussed the importance of detecting brain tumor discussed on detection and the import of this paper is:

SECN (For all the import of the import of the import of the import of the importance of the importance of segmented in the third phase. The purpose of this study was
only to use cranial MR images that have mass. The
classification exactness of cranial MR images is 96.2 % in the
experimental studies. The findings analyzed showe only to use cranıal MR images that have mass. The
classification exactness of cranial MR images is 96.2 % in the
experimental studies. The findings analyzed showed that the
efficiency of the suggested approach was higher t classitication exactness of cramal MR images is 96.2 % in the experimental studies. The findings analyzed showed that the efficiency of the suggested approach was higher than that of other recent literature studies. Experi experimental studies. The findings analyzed showed that the
efficiency of the suggested approach was higher than that of
other recent literature studies. Experimental results have shown
that it is an effective method that efficiency of the suggested approach was higher than that of
other recent literature studies. Experimental results have shown
that it is an effective method that can be used to diagnose
computer-aided brain tumors.
Nilesh other recent literature studies. Experimental results have shown
that it is an effective method that can be used to diagnose
computer-aided brain tumors.
Nilesh Bhaskarrao Bahadur et al. [26] initialized the Berkeley
Wavel that it is an effective method that can be used to diagnose
computer-aided brain tumors.
Nilesh Bhaskarrao Bahadur et al. [26] initialized the Berkeley
Wavelet Transformation and Support Vector Machine (BWT-
SVM) for image computer-aided brain tumors.

Nilesh Bhaskarrao Bahadur et al. [26] initialized the Berkeley

Wavelet Transformation and Support Vector Machine (BWT-

SVM) for image analysis for Magnetic Resonance images based

Brain Tumo Nilesh Bhaskarrao Bahadur et al. [26] initialized t
Wavelet Transformation and Support Vector Mac
SVM) for image analysis for Magnetic Resonance in
Brain Tumor identification and feature extracexplored histogram-based and Wavelet Transformation and Support Vector Machine (BWT-
SVM) for image analysis for Magnetic Resonance images based
Brain Tumor identification and feature extraction. They
explored histogram-based and texture-based feature SVM) for image analysis for Magnetic Resonance images based
Brain Tumor identification and feature extraction. They
explored histogram-based and texture-based features with an
approved MR brain tumor classification classif Brain Tumor identification and teature extraction. They
explored histogram-based and texture-based features with an
approved MR brain tumor classification classifier. The tests for
brain tumor diagnosis can be seen quickly explored histogram-based and texture-based features with an
approved MR brain tumor classification classifier. The tests for
brain tumor diagnosis can be seen quickly and accurately from
the experimental results in the var

Section 2 discussed the importance of detecting brain tumor and

background review. In section 3, a Fully Automated

Heterogeneous Segmentation using Support Vector Machine

(FAHS-SVM) has been proposed for brain tumor seg background review. In section 3, a Fully Automated

Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM) has been proposed for brain tumor segmentation

based on deep learning techniques. In section 4, the

a approved MR brain tumor classification classifier. The tests for
brain tumor diagnosis can be seen quickly and accurately from
the experimental results in the various images in contrast with
manual identification by clinic brain tumor diagnosis can be seen quickly and accurately from
the experimental results in the various images in contrast with
different performance variables show a better result with the
proposed algorithm by enhancing ot the experimental results in the various images in contrast with
manual identification by clinical experts or radiologists. The
different performance variables show a better result with the
proposed algorithm by enhancing o manual identification by clinical experts or radiologists. The
different performance variables show a better result with the
proposed algorithm by enhancing other parameters such as
PSNR, mean, MSE, precision, specificity, different performance variables show a better result with the
proposed algorithm by enhancing other parameters such as
PSNR, mean, MSE, precision, specificity, sensitivity,
coefficient of dice.
Jason J. Corso et al. [27] i proposed algorithm by enhancing other parameters such as
PSNR, mean, MSE, precision, specificity, sensitivity,
coefficient of dice.
Jason J. Corso et al. [27] introduced the Multilevel
Segmentation by Weighted Aggregation PSNR, mean, MSE, precision, specificity, sensitivity,
coefficient of dice.
Jason J. Corso et al. [27] introduced the Multilevel
Segmentation by Weighted Aggregation (MSWA) for brain
tumor segmentation. A new way of automat coefficient of dice.
Jason J. Corso et al. [27] introduced the Multilevel
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tumor segmentation. A new way of automatically segmenting
heterogeneous imaging data is to bri Jason J. Corso et al. [27] introduced the Multilevel
Segmentation by Weighted Aggregation (MSWA) for brain
tumor segmentation. A new way of automatically segmenting
heterogeneous imaging data is to bridge the gap between
a Jason J. Corso et al. $\lfloor 27 \rfloor$ introduced the Muttilevel
Segmentation by Weighted Aggregation (MSWA) for brain
tumor segmentation. A new way of automatically segmenting
heterogeneous imaging data is to bridge the gap b Segmentation by Weighted Aggregation (MSWA) for brain
tumor segmentation. A new way of automatically segmenting
heterogeneous imaging data is to bridge the gap between
affinity-based, bottom-up, and top-down model-based me tumor segmentation. A new way or automatically segmenting
heterogeneous imaging data is to bridge the gap between
affinity-based, bottom-up, and top-down model-based methods.
The paper's significant contribution is a Bayes

XXXXX: Brain Tumor Identification and Classification of MRI images using deep learning techniques (XXXXX)
XXXXX: Brain Tumor Identification and Classification of MRI images using deep learning techniques (XXXXX)
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Pradeep Kumar Mallick et al. [28] suggested the Deep wavelet

Pradeep Kumar Mallick et al. [28] suggested the Deep wavelet

Pradeep Kumar Mallick et al. [28] suggested the Deep wavelet

Pradeep Kumar Mallick et ELACCESS

Auto Encoder and Editive extraction in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation is
 Auto Encoder and Deep Neural Network (DWA-DNN) f EEE ACCESS

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Auto Encoder and Pradeep Kumar Mallick et al. [28] suggested the Deep wavelet

Auto Encoder and Deep Neural Network (DWA-DNN) for

Brain Magnetic Resonance image classification for cancer

recognition. This paper proposes a Deep Wavelet Au Pradeep Kumar Mallick et al. [28] suggested the Deep wavelet

Auto Encoder and Deep Neural Network (DWA-DNN) for Machines (SVM) classif

Brain Magnetic Resonance image classification for cancer use the support vector m

r Practice Rum Mallick et al. [28] suggested the Deep wavel

Auto Encoder and Deep Neural Network (DWA-DNN) for Machines (SVM) classification

Brain Magnetic Resonance image classification for cancer

the testport vector ma Auto Encorer and Deep Neural Network (DWA-DNN) for Machimes (SVM) classification frecognition. This paper proposes a Deep Wavelet Auto Encoder in many MRI modalities (DWA) image compression technique, which combines the se Brain Magnetic Resonance image classification for cancer

in many MRI modal

recognition. This paper proposes a Deep Wavelet Auto Encoder

in many MRI modal

(DWA) image compression technique, which combines the

segmenta recognition. This paper proposes a Deep wavelet Auto Encoder

(DWA) image compression technique, which combines the segmentation as a classif

Auto Encoder essential feature extraction function with the it is crucially fas (DWA) mage compression technique, winch contomines the segmentation as a cassince Auto Encocler essential feature extraction function with the it is crucially faster than ot
transform wavelet image decomposition method. Th Auto Encoder essential leature extraction function with
transform wavelet image decomposition method. The mixtur
both has a tremendous impact on the reduction of the feature
to continue to identify with DNN. The suggested both has a tremendous impact on the reduction of the feature set

to continue to identify with DNN. The suggested DWA-DNN

image classifier was reviewed, and a brain picture dataset was

taken. In comparison to other class to continue to identify with DNN. The suggested DWA-DNN

image classifier was reviewed, and a brain picture dataset was

taken. In comparison to other classifiers like Auto Encoder -

DNN or DNN, the efficient criterion fo mage classifier was reviewed, and a brain picture dataset was

taken. In comparison to other classifiers like Auto Encoder

DNN or DNN, the efficient criterion for the DWA-DNN was

that exist. The tests of the DWA-DNN appr taken. In comparison to other classifiers like Auto Encoder - 3. A Fully Automatic Fit

DNN or DNN, the efficient criterion for the DWA-DNN ways using Support Vector Mac

compared, and the approach suggested summarizes the

nay change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3016319, IEEE Access
nages using deep learning techniques (XXXXX)
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nages using deep learning techniques (XXXXX)

segmentation of the brain image, which is the Support Vector

Machine Transmark of the brain image, which is the Support Vector
Machines (SVM) classification process, has been utilized. To
Machines (SVM) classification process, has been utilized. To
in many MRI modulities. The proposed syste rages using deep learning techniques (XXXXX)
segmentation of the brain image, which is th
Machines (SVM) classification process, has
use the support vector machine (SVM) can ide
in many MRI modalities. The proposed
segment **Subsemination** of the brain image, which is the Support Vector Machines (SVM) classification process, has been utilized. To use the support vector machine (SVM) can identify brain tumors in many MRI modalities. The propos segmentation of the brain image, which is the Support Vector
Machines (SVM) classification process, has been utilized. To
use the support vector machine (SVM) can identify brain tumors
in many MRI modalities. The proposed segmentation of the brain image, which is the Support Vector
Machines (SVM) classification process, has been utilized. To
use the support vector machine (SVM) can identify brain tumors
in many MRI modelities. The proposed Machines (SVM) classification process, has been utilized. To
use the support vector machine (SVM) can identify brain tumors
in many MRI modalities. The proposed system reviews
segmentation as a classification issue. More a use the support vector machine (SVM) can identify brain tumors
in many MRI modalities. The proposed system reviews
segmentation as a classification issue. More accurately, because
it is crucially faster than other classifi

in many MRI modalities. The proposed system reviews
segmentation as a classification issue. More accurately, because
it is crucially faster than other classification techniques, because
of its robustness in generalization segmentation as a classification issue. More accurately, because
it is crucially faster than other classification techniques, because
of its robustness in generalization precipitation and its capacity
to manage volume info it is crucially faster than other classification techniques, because
of its robustness in generalization precipitation and its capacity
to manage volume information, the SVM classification method
ensures segmentation.
3. A of its robustness in generalization precipitation and its capacity
to manage volume information, the SVM classification method
ensures segmentation.
3. A Fully Automatic Heterogeneous Segmentation
using Support Vector Mach to manage volume information, the SVM classification method
ensures segmentation.
3. A Fully Automatic Heterogeneous Segmentation
using Support Vector Machine (FAHS-SVM):
In this study, a Fully Automatic Heterogeneous Segm ensures segmentation.

3. A Fully Automatic Heterogeneous Segmentation

using Support Vector Machine (FAHS-SVM):

In this study, a Fully Automatic Heterogeneous Segmentation

using Support vector machine (FAHS-SVM) for bra 3. A Fully Automatic Heterogeneous Segmentation
using Support Vector Machine (FAHS-SVM):
In this study, a Fully Automatic Heterogeneous Segmentation
using Support vector machine (FAHS-SVM) for brain tumor
detection and seg 3. A Fully Automatic Heterogeneous Segmentations and Support Vector Machine (FAHS-SVM):

In this study, a Fully Automatic Heterogeneous Segment

using Support vector machine (FAHS-SVM) for brain 1

detection and segmentati

i) Pre-Processing:
 EXECUTE: Resonance image parameters like the enhanced SNR ratio,
 EXECUTE: The primary operation of pre-processing is to enhance the Image, the elimination of unnecessary noise, and the under

qua From Tables Textraction & Decision

Making

Tables Making

Parameters like the enhanced SNR ratio, the

improvement of the visual look of the Magnetic Resonance

Image, the elimination of unnecessary noise, and the underse For a Extraction & Decision

Making

The Making

Resonance image parameters like the enhanced SNR ratio, the

improvement of the visual look of the Magnetic Resonance

Image, the elimination of unnecessary noise, and the u

based on a changed sigmoid feature to enhance the SNR ratio
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based on a changed sigmoid feature to enhance th And the shas been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication
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Skull Stripping: FICE ACCESS

Skull stripping is a major biomedical image analysis procedure.

Skull stripping is a major biomedical image analysis procedure.

In Skull Stripping:

Skull stripping is a major biomedical image analysis proce **IEEE** ACCESS xxxxx: Brain Tumor Identification and Classification of MRI images using deep learning techniques (XX

based on a changed sigmoid feature to enhance the SNR ratio

and, therefore, the quality of the raw Magne **IEEE** *ACCESS* xxxxx: Brain Tumor Identification and Classification of MRI images using deep learning techniques (

based on a changed sigmoid feature to enhance the SNR ratio

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based on a changed sigmoid feature to enhance the SNR ratio

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Skull stri based on a changed sigmoid feature to enhance the SNR ratio

and, therefore, the quality of the raw Magnetic Resonance

images.
 ii) Skull Stripping:

Skull stripping is a major biomedical image analysis procedure.

It i based on a changed sigmoid feature to enhance the SNR ratio
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 ii) Skull Stripping:
 Eximiliarity and Skull stripping is a major biomedical image analysis based on a changed sigmoid feature to enhance the SNR ratio

and, therefore, the quality of the raw Magnetic Resonance

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 ii) Skull stripping:

Skull stripping is a major biomedical image analysis procedure.

It i and, therefore, the quality of the raw Magnetic Resonance

images.
 ii) Skull stripping:
 Skull stripping is a major biomedical image analysis procedure.

It is essential for a practical test of brain tumors from MR

i stripping. **is a set of the sesential for a practical test of brain tumors from MR** images, in which all non-brain tissue in brain imaging is removed. Skull stripping Skull stripping is a major biomedical image analysis procedure.

It is essential for a practical test of brain tumors from MR

images, in which all non-brain tissue in brain imaging is

removed. Skull stripping enables add It is essential for a practical test of brain tumors from MR
images, in which all non-brain tissue in brain imaging is
termoved. Skull stripping enables additional brain itssues like
skull, skin, and fat to be extracted in images, in which all non-brain tissue in brain imaging is

removed. Skull stripping enables additional brain insues like

skull, skin, and fat to be extracted in brain images. There are a

variety of skull stripping techn

removed. Skull stripping enables additional brain tissues like
skull, skin, and fat to be extracted in brain images. There are
variety of skull stripping techniques available, some of which
are common include the use of an skull, skin, and fat to be extracted in brain images. There are a variety of skull stripping techniques available, some of which
the ser common include the use of an automated skull stripping by
image contour, segmentation variety of skull stripping techniques available, some of which
are common include the use of an automated skull stripping by

image contour, segmentation-and morphological stripping of the

skull, and hectographic analysis are common include the use of an automated skull stripping by

incept contour, segmentation-and morphological stripping of the

skull, and hectographic analysis or threshold-based skull

stripping.

iii) **Morphological Ope** image contour, segmentation-and morphological stripping of the
skull, and hectographic analysis or threshold-based skull
stripping.

iii) **Morphological Operation and Segmentation:**

In the first stage, the pre-processed skull, and hectographic analysis or threshold-based skull
stripping.
 iii) Morphological Operation and Segmentation:

In the first stage, the pre-processed brain Magnetic Resonance

image will be transformed into a binar stripping.
 iii) Morphological Operation and Segmentation:

In the first stage, the pre-processed brain Magnetic Resonance

image will be transformed into a binary image with a threshold

of 128 for the cutoff. Pixel val **III) Morphological Operation and Segmentation:**

In the first stage, the pre-processed brain Magnetic Resonance

image will be transformed into a binary image with a threshold

of 128 for the cutoff. Pixel values higher **III) Morphological Operation and Segmentation:**

In the first stage, the pre-processed brain Magnetic Resonance

image will be transformed into a binary image with a threshold

of 128 for the cutoff. Pixel values higher In the first stage, the pre-processed brain Magnetic Resonance

image will be transformed into a binary image with a threshold

of 128 for the cutoff. Pixel values higher than the specified

thresholds

black; these two a In me first stage, the pre-processed orain Magnetic Kesonance and All wavelet due to the segmentation figure 3(c) Sagittal images and its segmentation figure 3(c) be and its segmentation figure 3(c) and its segmentation f mage will be transformate into a binary image with a threshold
thresholds are mapped as white, with other regions marked as
the discasse. In the second stage, an erosion process of
morphology is used to extract white pixe or 128 for the cutoff. Pixel values higher
thresholds are mapped as white, with other
black; these two allow various regions to be
the disease. In the second stage, an en
morphology is used to extract white pixel
eroded ar

segmentation

Figure 3: Fully Automatic Heterogeneous segmentation (a) Axial image and its segmentation (b) Coronal image and its segmentation (c) Sagittal image and its segmentation
A wavelet is a function stated over a limited time i **Figure 3: Fully Automatic Heterogeneous segmentation** (a) Axial image and its segmentation (b) Coronal image and its segmentation (c) Sagittal image and its segmentation A wavelet is a function stated over a limited time Figure 3: Fully Automatic Heterogeneous segmentation (a) Axial image and its segmentation (b) Coronal image and its segmentation (c) Sagittal image and its segmentation A wavelet is a function stated over a limited time i **3(c)**

Figure 3: Fully Automatic Heterogeneous segmentation (a) Axial image and its segmentation (b) Coronal image and its segmentation (c) Sagittal image and its segmentation

A wavelet is a function stated over a limit **State of the Separation** (a) Axial image and its segmentation (b) Coronal image and its segmentation (c) Sagittal image and its segmentation (c) Sagittal image and its segmentation A wavelet is a function stated over a l **3(c)**

Figure 3: Fully Automatic Heterogeneous segmentation (a) Axial image and its

segmentation (b) Coronal image and its segmentation (c) Sagittal image and its

segmentation

A wavelet is a function stated over a lim A wavelet is a function stated over a limited time interval with
an average value of null. The transformation wavelet method is
used to create features, operators, and data into different
frequency components, which allow A wavelet is a function stated over a limited time
an average value of null. The transformation wave
used to create features, operators, and data i
frequency components, which allows every com
discretely studied. All wave and to create features, operators, and data into different
frequency components, which allows every component to be
discretely studied. All wavelets are produced from a basic
wavelet $\varphi(r)$ utilizing the translation and uency components, which allows every component to be
retely studied. All wavelets are produced from a basic
relet $\varphi(r)$ utilizing the translation and scaling procedure
ed by equation (1); A simple wavelet is called a mo discretely studied. All wavelets are produced from a basic
wavelet $\varphi(r)$ utilizing the translation and scaling procedure
stated by equation (1); A simple wavelet is called a mother
wavelet due to the other wavelets it i

$$
\varphi_{w,\tau} = \frac{1}{\sqrt{w}} \varphi \left(\frac{r - \tau}{w} \right) \tag{1}
$$

 $\alpha_{\theta}^{\varphi}$ is a piecewise constant wavelet $\varphi(r)$ utilizing the translation and scaling proced
stated by equation (1); A simple wavelet is called a mot
wavelet due to the other wavelets it is the point of origin.
 $\varphi_{w,\tau} = \frac{1}{\sqrt{w}} \varphi\left(\frac{r-\tau}{w}\right)$ (1)
 $\varphi_{w,\tau} = \frac{1}{\sqrt{w}} \varphi\left(\frac{r-\tau}{w}\right)$ (1)
As shown in equation (1), where w and τ are the translation and
scale factors correspondingly.
The efficient way of the depiction of image transformation and
 α_{θ}^{θ} is a As shown in equation (1), where w and τ are the translation and
scale factors correspondingly.
The efficient way of the depiction of image transformation and
 α_{θ}^{θ} is a piecewise constant function and it generat As shown in equation (1), where w and τ are the translation and
scale factors correspondingly.
The efficient way of the depiction of image transformation and
 α_{θ}^{θ} is a piecewise constant function and it generat scale factors correspondingly.

The efficient way of the depiction of image transformation and α_p^{θ} is a piecewise constant function and it generates a different pixel position in the 2D plane via translation and sca

$$
\alpha_{\theta}^{\varphi}(\tau,w) = \frac{1}{w^2} \alpha_{y}^{\varphi}(3^{w}(y-j), 3^{w}(x-i)), \qquad (2)
$$

term sufficiently depicts an image mean value; in the si
term, the coefficient value is shown
 $\alpha_0 = \frac{1}{\sqrt{9}} \left[\nu \left(\frac{y}{3}, \frac{x}{3} \right) \right]$ (3)
VOLUME XX, 2019
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$$
\alpha_0 = \frac{1}{\sqrt{9}} \left[\nu \left(\frac{y}{3}, \frac{x}{3} \right) \right] \tag{3}
$$

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The morphological procedure is used for extracting the limits of

the brain images. Conceptuall EEE ACCESS

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The morphological procedure is used for extracting the limits of

the brain images. Conceptually, **FEE ACCESS** xxxxx: Brain Tumor Identification and Classification of MRI images using deep learning techniques
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The morphological procedure is used for extracting the limits of

The morphological procedure is used for extracting the limits of

the brain images. Conceptually, only the relative order of the

pixel values **FIRE ACCESS** XXXXX: Brain Tumor Identification and Classification of MRI images using deep learning technique
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XXXXX: Brain Tumor Identification and Classification of MRI images usi **IEEE** ACCESS xxxxx: Brain Tumor Identification and Classification of MRI images using deep learning techniques (X)
The morphological procedure is used for extracting the limits of
the brain images. Conceptually, only the **IEEE** ACCESS xxxxx: Brain Tumor Identification and Classification of MRI images using deep learning tects.

The morphological procedure is used for extracting the limits of

the brain images. Conceptually, only the relat **IEEE** ACCESS xxxxx: Brain Tumor Identification and Classification of MRI images using deep learning techniques ()

The morphological procedure is used for extracting the limits of

the brain images. Conceptually, only th **EXECUTE:** ACCUTE XXXX: Brain Tumor Identification and Classification of MRI images using deep learning techniques (X

The morphological procedure is used for extracting the limits of

the brain images. Conceptually, only The morphological procedure is used for extracting
the brain images. Conceptually, only the relative
pixel values is restructured in morphological operat
mathematical values, and only binary images can,
processed. Dilatati the brain images. Conceptually, only the relative pixel values is restructured in morphological opermathematical values, and only binary images can processed. Dilatation operations are intended to into an object's boundary pixel values is restructured in morphological operation, not their
mathematical values, and only binary images can, therefore, be
processed. Dilatation operations are intended to insert pixels
into an object's boundary ar mathematical values, and only binary images can, therefore, be

processed. Dilatation operations are intended to insert pixels the reproductions that can be

into an object boundary zone. Addition and pixel removal operat processed. Dilatation operations are intended to insert pixels

into an object's boundary zone. Addition and pixel removal operations function defines energy

object boundary zone. Addition and pixel removal operations fu

into an object's boundary area and to delete pixels from the calculating an image's similary of condrary zone. Addition and pixel removal operations function defines energy, it is depend on the structuring aspect of the s object boundary zone. Addition and pixel removal operations

depend on destinction defines energy, it into the solution of structuring aspect of the selected picture from or

provided by the proposed procedure are shown f depend on the structuring aspect of the selected picture from or

to the boundary region of objects. The results of the experiment

provided by the proposed procedure are shown for the

tumor region extracted.
 Contrast: to the boundary region of objects. The results of the experiment
provided by the proposed procedure are shown for the
segmented results of the CSF, GM, and WM, classes, and the
tumor region extracted.
C. Contrast: Contr provided by the proposed procedure are shown for the

segmented results of the CSF, GM, and WM, classes, and the
 G. Contrast: Contrast is a cal
 iv) Feature Extraction:
 C. Contrast: Contrast is a cal
 iv) Feature segmented results of the CSF, GM, and WM, classes, and the

tumor region extraction:
 iv Feature Extraction:

It is the set of superior-level image details, including contrast,

It is the set of superior-level image det tumor region extracted.
 C. Contrast: Contrast is a cal
 iv) Feature Extraction:

It is the set of superior-level image details, including contrast,
 $G = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y-x)^2 f(y,x)$

shape, color, and texture. I **Example 16 Extraction:** The mathematical formula. The mathematical formula. The mathematical formula. The mathematical formula. It is utilized efficiently by choosing prominent features to The maximize the precision of It is the set of superior-level image details, including contrast,

shape, color, and texture. In reality, texture analysis is a crucial

attribute for the vision and machine learning systems of humans.
 H. Homogeneity o It is the set of superior-level image details, including contrast, $G = \sum_{y=0}^{\infty} \sum_{x=0}^{\infty} (y-x)^x f(y,x)$
shape, color, and texture. In reality, texture analysis is a crucial
diffuse of the vision and machine learning syst **B.** Standard Deviation: The SD is the second central moment

fractures in the second by textual observations and analyses, as well as the

fractures. The diagnosis of the tumor (tumor stage) could be $IDM = \sum_{y=0}^{n-1} \sum_{x$

image.

$$
N = \left(\frac{1}{n \times m}\right) \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y, x) \tag{4}
$$

Example 12 Follogy the term of enhanced by textual observations and therapy response assessment. Some of tound below in the mathematical formu **A. Mean:** The mean of an image is de an image total pixel values divide Features. The diagnosis of the tumor (tumor stage) could be

features. The diagnosis of the tumor (tumor stage) could be

therapy response assessment. Some of the useful features can be

therapy response assessment. Some Figure 2. The variables of the calculate of inhomogeneity.
 Probability distribution and to calculate of inhomogeneity.
 A. Mean: The mean of an image is determined by summing up
 A. Mean: The mean of an image is de Extrained by summing and the image assessment. Some of the useful features can be

found below in the mathematical formula.
 A. Mean: The mean of an image is determined by summing up

alignment of the image, and image t **EXECUTE:** The mean of an image is determined by summing to found below in the mathematical formula.
 A. Mean: The mean of an image is determined by summing to an image total pixel values divided by the total pixel valu $\frac{m-1}{x=0}f(y,x)$ (4) *L*
 iation: The SD is the second central moment

served population can be described as the C

ution and to calculate of inhomogeneity. A

s a good level of intensity and great contrast

of an im **C.** Entropy: Entropy is measured to characterize the textured is a said to be coardinated Deviation: The SD is the second central moment in which an observed population can be described as the $C = \frac{\sum_{y=0}^{n-1} \sum_{x=0}^{m N = (\frac{1}{n \times m}) \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x)$ (4) the
 B. Standard Deviation: The SD is the second central moment

in which an observed population can be described as the

porobability distribution and to calculate of inho **D. Skewness:** Skewness is a symmetry attribute or symmetry
 $D = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) \log_2 f(y,x)$ (5)
 D. Skewness: Skewness is a symmetry attribute or symmetry
 $D = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) \log_2 f(y,x)$ (6)
 D. Ske

$$
SD(\rho) = \sqrt{\left(\frac{1}{n \times m}\right) \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (f(y,x) - N)^2}
$$
 (5)

$$
D = -\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) \log_2 f(y,x) \qquad (6)
$$

better value shows a good level of i
between the edges of an image.
 $SD(\rho) = \sqrt{\left(\frac{1}{n \times m}\right) \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (f(y,x))}$
C. Entropy: Entropy is measured to
image randomness and is defined as
 $D = -\sum_{y=0}^{n-1} \sum_{x=0}^{m-1$ value shows a good level of intensity and great co
 = $\sqrt{\left(\frac{1}{n \times m}\right) \sum_{y=0}^{m-1} \sum_{x=0}^{m-1} (f(y,x) - N)^2}$ (5)
 tropy: Entropy is measured to characterize the tex

randomness and is defined as
 $\sum_{y=0}^{n-1} \sum_{x=0}^{m$ probability distribution and to calculate of inhomogeneity. A

better value shows a good level of intensity and great contrast

better value shows a good level of intensity and great contrast
 $SD(\rho) = \sqrt{\left(\frac{1}{n \times m}\right) \sum_{y=0$ between the edges of an image.
 $SD(\rho) = \sqrt{\left(\frac{1}{n \times m}\right) \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (f(y,x) - N)^2}$
 C. Entropy: Entropy is measured to characte image randomness and is defined as
 $D = -\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) \log_2 f(y,x)$ (6)
 *z*_{x=0} *f*(*y*,*x*)*log ₂ <i>f*(*y*,*x*) (6) coa

ess: Skewness is a symmetry attribute or symmetry

the Skewness is called $W_l(Y)$ and defined as a random $H =$
 $\frac{1}{n \times m}$ $\frac{\sum (f(y,x)-N)^3}{SD^3}$ (7) the imp

is: The par **E. Entropy:** Entropy is measured to characterize the textured

inage randomness and is defined as
 $D = -\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) \log_2 f(y,x)$ (6)
 E. Skewness: Ekewness is a symmetry attribute or symmetry
 E. Kurtosis: C. Entropy: Entropy is measured to characterize the textured

image randomness and is defined as
 $D = -\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) \log_2 f(y,x)$ (6) with a smaller number of

consers. Skewness is a symmetry attribute or sy transformations and is defined as
 $D = -\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) \log_2 f(y,x)$ (6) with a smaller nu
 D. Skewness: Skewness is a symmetry attribute or symmetry meaning is:

absence. The Skewness is called $W_l(Y)$ and defin

$$
W_l(Y) = \left(\frac{1}{n \times m}\right) \frac{\sum (f(y, x) - N)^3}{SD^3}
$$
 (7)

 $W_l(Y) = \left(\frac{1}{n \times m}\right) \frac{\sum (f(y, x) - N)^3}{5D^3}$ (7) the following criteria of quality evaluation are required
 E. Kurtosis: The parameter Kurtosis defines the shape of a

random variable likelihood distribution. The Kurtosis

$$
L(Y) = \left(\frac{1}{n \times m}\right) \frac{\sum (f(y,x)-N)^4}{SD^4}
$$

may change prior to final publication. Citation information: DOI :

nages using deep learning techniques (XXXXX)
 $L(Y) = \left(\frac{1}{n \times m}\right) \frac{\sum (f(y,x)-N)^4}{SD^4}$
 F. Energy: Energy can be stated as the

reproductions that can be *× [−]* **F. Energy:** Energy can be stated as the amount of pixel-pair
 F. Energy: Energy can be stated as the amount of pixel-pair
 F. Energy: Energy can be stated as the amount of pixel-pair
 F. Energy: Energy can be state reproductions that can be quantified. Energy is a parameter for the Haralic stated as the amount of pixel-pair reproductions that can be quantified. Energy is a parameter for calculating an image's similarity. If the Hara may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3016319, IEEE Access

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nages using deep learning techniques (XXXXX)
 $L(Y) = \left(\frac{1}{n \times m}\right) \frac{\sum (f(y,x)-N)^4}{SD^4}$
 F. Energy: Energy can be stated as hay and the polarity is stated as the amount of pixel
 $L(Y) = \left(\frac{1}{n \times m}\right) \frac{\sum (f(y.x) - N)^4}{SD^4}$
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reproductions that can be quantified. Energy is a paramete

calculat *L*(*Y*) = $\left(\frac{1}{n \times m}\right) \frac{\sum (f(y, x) - N)^4}{SD^4}$
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reproductions that can be quantified. En
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moment and is st $L(Y) = \left(\frac{1}{n \times m}\right) \frac{\sum (f(y,x)-N)^4}{SD^4}$
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calculating an image's similarity. If the Haralick's G $L(Y) = \left(\frac{1}{n \times m}\right) \frac{\sum (f(y, x) - N)^4}{SD^4}$
 F. Energy: Energy can be stated as the amount of pixel-pair

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calculating an image's similarity. If the Haralick's

$$
Em = \sqrt{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f^2(y,x)}
$$
 (9)

$$
G = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y-x)^2 f(y,x) \tag{10}
$$

function defines energy, it is known

moment and is stated as
 $Em = \sqrt{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f^2(y,x)}$
 G. Contrast: Contrast is a calculation

neighbor of a pixel over the image.
 $G = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y - x)^2 f(y,x)$ (
 Homogeneity or **Inverted moment of difference (IDM)**:
 H. Homogeneity sates imilarity. If the Haralick's GLCM

function defines energy, it is known as an angular second

moment and is stated as
 $Em = \sqrt{\sum_{y=0}^{n-1} \sum_{x=$ calculating an image's similarity. If the Haralick's GLCM
function defines energy, it is known as an angular second
moment and is stated as
 $Em = \sqrt{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f^2(y,x)}$ (9)
G. Contrast: Contrast is a calculation o function defines energy, it is known as an angular second
moment and is stated as
 $Em = \sqrt{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f^2(y,x)}$ (9)
G. Contrast: Contrast is a calculation of the intensity and the
neighbor of a pixel over the image moment and is stated as
 $Em = \sqrt{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f^2(y,x)}$ (9)
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 $G = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y-x)^2 f(y,x)$ (10)
 H. Homogeneit *neighbor of a pixel over the image.*
 $G = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y - x)^2 f(y,x)$ (10)
 H. Homogeneity or Inverted moment

The IDM is a calculation of an image's l

could have a single value or set of benefi

or not the mod **nogeneity or Inverted moment of difference (II**)
M is a calculation of an image's local consistency
ave a single value or set of benefits to identify wh
he model is textured.
 $\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} \frac{1}{1+(y-x)^2} f(y,x)$ **G. Contrast:** Contrast is a calculation of the intensity and the neighbor of a pixel over the image.
 $G = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y-x)^2 f(y,x)$ (10)
 H. Homogeneity or Inverted moment of difference (IDM):

The IDM is a cal neighbor of a pixel over the image.
 $G = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y-x)^2 f(y,x)$ (10)
 H. Homogeneity or Inverted moment of difference (IDM):

The IDM is a calculation of an image's local consistency IDM

could have a single $G = \sum_{y=0}^{m-1} \sum_{x=0}^{m-1} (y-x)^2 f(y,x)$ (10)
 H. Homogeneity or Inverted moment of difference (IDM):

The IDM is a calculation of an image's local consistency IDM

could have a single value or set of benefits to identify The IDM is a calculation of an image's local consistency IDM
could have a single value or set of benefits to identify whether
or not the model is textured.
 $IDM = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} \frac{1}{1+(y-x)^2} f(y,x)$ (11)
I. Direction

$$
IDM = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} \frac{1}{1 + (y - x)^2} f(y, x)
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Could have a single value or set of bene

or not the model is textured.
 IDM = $\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} \frac{1}{1+(y-x)^2} f(y,x)$ (1
 I. Direction moment: Direction moment

the image measured by taking into

alignment of th aave a single value or set of benefits to identity whe

the model is textured.
 $\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} \frac{1}{1+(y-x)^2} f(y,x)$ (11)
 ction moment: Direction moment is a textural feature

age measured by taking into account could have a single value or set of benefits to identify whether
or not the model is textured.
 $IDM = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} \frac{1}{1+(y-x)^2} f(y,x)$ (11)
 I. Direction moment: Direction moment is a textural feature of

the ima

$$
DM = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) |y - x|
$$
 (12)

$$
C = \frac{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y,x) f(y,x) - N_y N_x}{\rho_y \rho_x} \tag{13}
$$

*n −<i>−−n=<i>n******nnn<i>nnnnn<i>nnn<i>nnnnn<i>nn<i>nn<i>nn<i>nn<i>n* $=\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) |y-x|$ (12)
 orrelation: The correlation feature explains and dete

patial dependencies between the pixels,
 $\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y,x) f(y,x) - N_y N_x$ (13)

shown in equation (12) where ρ_y a **I. Direction moment:** Direction moment is a textural feature of
the image measured by taking into account the angle of
alignment of the image, and it is defined as
 $DM = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) |y-x|$ (12)
J. Correlatio Solution EXECT is a textual relation of the image measured by taking into account the angle of alignment of the image, and it is defined as $DM = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) |y-x|$ (12)
 J. Correlation: The correlation and $DM = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) |y-x|$ (12)

J. Correlation: The correlation feature explains and determines

the spatial dependencies between the pixels,
 $C = \frac{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y,x) f(y,x) - N_y N_x}{\rho_y \rho_x}$ (13)

As sh $DM = \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x) |y-x|$ (12)

J. Correlation: The correlation feature explained the spatial dependencies between the pixels,
 $C = \frac{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y,x) f(y,x) - N_y N_x}{\rho_y \rho_x}$ (13)

As shown in equation (12

 $DM = \sum_{y=0} \sum_{x=0}^{n-1} f(y,x) [y-x]$ (12)
 J. Correlation: The correlation feature explains and determines

the spatial dependencies between the pixels,
 $C = \frac{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y,x) f(y,x) - N_y N_x}{\rho_y \rho_x}$ (13)

As shown in **J. Correlation:** The correlation feature explains and determines
the spatial dependencies between the pixels,
 $C = \frac{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y.x)f(y.x) - N_yN_x}{\rho_y \rho_x}$ (13)
As shown in equation (12) where ρ_y and N_y and are **J. Correlation:** The correlation feature explains and determines
the spatial dependencies between the pixels,
 $C = \frac{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y.x) f(y.x) - N_y N_x}{\rho_y \rho_x}$ (13)
As shown in equation (12) where ρ_y and N_y and ar the spatial dependencies between the pixels,
 $C = \frac{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y.x) f(y.x) - N_y N_x}{\rho_y \rho_x}$ (13)

As shown in equation (12) where ρ_y and N_y and are the

standard deviation and mean in the horizontal spatial dom $C = \frac{\sum_{y=0}^{n-1} \sum_{x=0}^{m-1} (y,x) f(y,x) - N_y N_x}{\rho_y \rho_x}$ (13)

As shown in equation (12) where ρ_y and N_y and are the

standard deviation and mean in the horizontal spatial domain

and ρ_x and N_x are standard deviation $C = \frac{\sum_{y=0}^{n} \sum_{x=0}^{n} (y, x)f(y, x)-N_yN_x}{\rho_y \rho_x}$ (13)
As shown in equation (12) where ρ_y and a
standard deviation and mean in the horizonta
and ρ_x and N_x are standard deviation and me
spatial domain.
K. Coarseness spatial domain.
 K. Coarseness: Coarseness is the text

is the measure of roughness. For a

texture is said to be coarser than the o

with a smaller number of texture attribucoarser. Smaller coarseness values I

meaning Standard deviation and mean in the individual spatial domain
and ρ_x and N_x are standard deviation and mean in the vertical
spatial domain.
K. Coarseness: Coarseness is the textural analysis of an image
is the measu **EXECUTE:** The Structural similarity Index (SSIM): SSIM is a
percential metric in structural are realistic of a matter is said to be coarser than the one with a higher number
with a smaller number of texture attributes. T **K. Coarseness:** Coarseness is the textural analysis of an image
is the measure of roughness. For a fixed window size, the
texture is said to be coarser than the one with a higher number
with a smaller number of texture a **L. Coalsenses.** Coalsenses is the textural analysis of all image
is the measure of roughness. For a fixed window size, the
texture is said to be coarser than the one with a higher number
with a smaller number of texture perceptual to the coarser than the one with a higher number
twith a smaller number of texture attributes. The rougher layer is
coarser. Smaller coarseness values have fine textures. The
meaning is:
 $H = \frac{1}{2^{n+m}} \sum_{y=0}^{n-$ Exite is said to be coarser than the one with a migher number
with a smaller number of texture attributes. The rougher layer is
coarser. Smaller coarseness values have fine textures. The
meaning is:
 $H = \frac{1}{2^{n+m}} \sum_{y=0}^{n$

$$
H = \frac{1}{2^{n+m}} \sum_{y=0}^{n-1} \sum_{x=0}^{m-1} f(y,x)
$$
 (14)

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of image processing will result in quality degradation. The calculated by purely numeric

meaning is that mach

The phase been accepted for publication in a future issue of this journal, but has not been fully edi-
\n**IEEE** *ACCESS* ' XXXX'. Brain Tumor Identification and Classification.
\nIn the image processing will result in quality degradation.
\nmeaning is that
\n
$$
SSIM = \left(\frac{\rho_{yx}}{\rho_{y}\rho_{x}}\right) \left(\frac{2\overline{yx}}{(\overline{y}^2) + (\overline{x}^2) + B_1}\right) \left(\frac{2\rho_{y}\rho_{x}}{(\rho_{y})^2 + (\rho_{x})^2 + B_2}\right)
$$
\n(15)
\nA higher SSIM value means that luminance, contrast, structural quality are maintained very efficiently.
\nM. Mean square error: MSE is fidelity image or signal fid

IEEE *ACCESS* xxxxx: Brain Tumor Identification and Class

of image processing will result in quality degrada

meaning is that
 $SSIM = \left(\frac{\rho_{yx}}{\rho_{y}\rho_x}\right) \left(\frac{2yx}{(y^2)+(x^2)+B_1}\right) \left(\frac{2\rho_y\rho_x}{(\rho_y)^2+(\rho_x)^2+B_2}\right)$ (1

A higher S **SEE ACCESS** xxxxx: Brain Tumor Identification and Classification of MRI images usi

of image processing will result in quality degradation. The calcula

machir
 $SSIM = \left(\frac{\rho_{yx}}{\rho_y \rho_x}\right) \left(\frac{2y\bar{x}}{(y^2)+(x^2)+B_1}\right) \left(\frac{2\rho_y \rho$ **IEEE** ACCESS xxxx. Brain Tumor Identification and Classification of MRI images using deep learning technique of image processing will result in quality degradation. The calculated by purely num machine has low calculatio **THEF ACCESS** XXXX: Brain Tumor Identification and Classification of MRI images using deep learning techniques (X)

of image processing will result in quality degradation. The calculated by purely numerical

machine has l of image processing will result in quality degradation. The calculated by purely numer meaning is that machine has low calculation seeks to provide a quantitative score.

A higher SSIM value means that luminance, contrast of image processing will result in quality degradation. The calculated by purely nu

machine has low calculated $SSIM = \left(\frac{\rho_{yx}}{\rho_{y\rho_x}}\right) \left(\frac{2\sigma_x}{(\rho_y)^2 + (\rho_x)^2 + B_1}\right) \left(\frac{2\rho_y \rho_x}{(\rho_y)^2 + (\rho_x)^2 + B_2}\right)$ (15) The FWM algorithm i of image processing will result in quality degradation. The calculated by purely numer
meaning is that
 $SSIM = \left(\frac{\rho_{yx}}{\rho_{y}\rho_x}\right) \left(\frac{2\sigma_y}{(\sigma^2) + (\bar{x}^2) + \bar{B}_1)}\right) \left(\frac{2\rho_y \rho_x}{(\rho_y)^2 + (\rho_x)^2 + \bar{B}_2}\right)$ (15) The SVM algorithm i meaning is that
 $SSIM = \left(\frac{\rho_{yx}}{\rho_{y}\rho_x}\right) \left(\frac{2\bar{y}x}{(\bar{y}^2)+(x^2)+B_1}\right) \left(\frac{2\rho_y\rho_x}{(\rho_y)^2+(\rho_x)^2+B_2}\right)$ (15)

A higher SSIM value means that luminance, contrast, as

structural quality are maintained very efficiently.
 M. structural quality are maintained very effic.
 M. Mean square error: MSE is fidelity in

To find a correlation or truth between two

image fidelity calculation seeks to provid

When Mean Square Error is measured, on

to If quality are maintained very efficiently.
 n square error: MSE is fidelity image or signal fidelity. kernel function has been used in the Gaussian kernel

a correlation or truth between two models, the signal or

ligh A higher SSIM value means that luminance, contrast, and nonlinear divisive goal into structural quality are maintained very efficiently.
 M. Mean square error: MSE is fidelity image or signal fidelity. kernel function h structural quality are maintained very efficiently.
 M. Mean square error: MSE is fidelity image or signal fidelity.

To find a correlation or truth between two models, the signal or

ligh-dimensions

image fidelity cal to be impure, the other to be distorted or manipul-
means and described as "original."
 $MSE = \frac{1}{N \times M} \sum \sum (f(y,x) - f^T(y,x))^2$ (
 N. Peak Signal to Noise Ratio: The PSNR is a cal

for the evaluation of the accuracy of the ima mage indelity calculation seeks to provide a quantitative score.

When Mean Square Error is measured, one image is presumed two training is known as the

to-he impure, the other to be distorted or manipulated by some

mea When Mean Square Error is measured, one image is pre
to be impure, the other to be distorted or manipulated by
means and described as "original."
 $MSE = \frac{1}{N \times M} \sum \sum (f(y,x) - f^T(y,x))^2$ (16)
N. **Peak Signal to Noise Ratio:** The

$$
MSE = \frac{1}{N \times M} \sum \sum (f(y, x) - f^{T}(y, x))^{2}
$$
 (16)

$$
PSBR \ in \ db = 20 \ log_{10} \frac{2^{m} - 1}{MSE} \tag{17}
$$

SVM

```
MSE = \frac{1}{N \times M} \sum \int (f(y,x) - f^{T}(y,x))^2<br>
N. Peak Signal to Noise Ratio: The PSNR is<br>
for the evaluation of the accuracy of the image<br>
PSBR in db = 20 \log_{10} \frac{2^{m-1}}{MSE}<br>
An excellent signal-to-noise ratio suggests 1
  N. Peak Signal to Noise Ratio: The PSNR is a c<br>for the evaluation of the accuracy of the image rec<br>PSBR in db = 20 log <sub>10</sub> \frac{2^{m}-1}{MSE} (17<br>An excellent signal-to-noise ratio suggests lowe<br>and a higher PSNR value.<br>
  N. Peak Signal to Noise Ratio: The PSNF<br>for the evaluation of the accuracy of the im<br>PSBR in db = 20 log_{10} \frac{2^m-1}{MSE}<br>An excellent signal-to-noise ratio suggest<br>and a higher PSNR value.<br>Algorithm 1: Extreme learni
  An excellent signal-to-noise ratio suggests lower<br>and a higher PSNR value.<br><br>Algorithm 1: Extreme learning machine algorith<br>SVM<br>Input: 1, x<br>Cutput: 1, x<br>For (i=0)<br>f(x) = Z^R \omega(x) + \alpha<br>For (j=0)<br>l(x_j, x_i) = \exp[-\delta ||x_j - x_iPSBR in db = 20 \log_{10} \frac{2^{m}-1}{MSE}<br>
An excellent signal-to-noise ratio suggest<br>
and a higher PSNR value.<br>
Algorithm 1: Extreme learning machine<br>
SVM<br>
Input: j,I<br>
Output: l, x<br>
For (i=0)<br>
f(x) = Z^R \omega(x) + \alpha<br>
For 
  and a nigher PSNK value.<br>
Algorithm 1: Extreme learning i<br>
SVM<br>
Input: 1, x<br>
For (i=0)<br>
f(x) = Z^R \omega(x) + a<br>
For (j=0)<br>
l(x_j, x_i) = \exp \left[-\delta ||x_j - x_i||^2\right]<br>
If (l=0)<br>
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} (\exp \left[-\delta \frac{\sinh(\theta)}{\sinh(\theta)}\right]<br>
Else (l>0
                         a nigher PSNK value.<br>
orithm 1: Extreme learning machine algorithm based<br>
\Lambda<br>
(i=0)<br>
= Z^R \omega(x) + \alpha<br>
(j=0)<br>
\omega, x_i) = \exp \left[-\delta ||x_j - x_i||^2\right]<br>
=0)<br>
\omega, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left(\exp \left[-\delta ||x_j - x_i||^2\right]\right)<br>
(l>0)<br>
\omega, x_i) 
                                                                                                                                                                    \mathbf{z} and 
  An excellent signal-to-noise ratio sugge<br>
and a higher PSNR value.<br>
Algorithm 1: Extreme learning machisol SVM<br>
Input: j,I<br>
Output: l, x<br>
For (i=0)<br>
f(x) = Z^R \omega(x) + \alpha<br>
For (j=0)<br>
l(x_j, x_i) = \exp[-\delta ||x_j - x_i||^2]<br>
If (l
  SVM<br>
Input: j,I<br>
Output: l, x<br>
For (i=0)<br>
f(x) = Z^R \omega(x) + a<br>
For (j=0)<br>
l(x_j, x_i) = \exp \left[-\delta ||x_j - x_i||^2\right]<br>
If (l=0)<br>
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left(\exp \left[-\delta \right]<br>
Else (l>0)<br>
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left(\exp \left[-\delta \right]<br>
End if<br>
End 
                         \mathbf{t}_k(x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left( \exp \left[ -\delta \left\| x_j - x_i \right\|^2 \right] \right)As shown<br>
and I<br>
dentified in and I<br>
\delta ||x_j - x_i||^2<br>
y_i \in N_i \left( \exp \left[ -\delta ||x_j - x_i||^2 \right] \right)<br>
y_i \in N_i \left( \exp \left[ -\delta ||x_j - x_i||^2 \right] \right) = 1Example 1 Extreme learning machine<br>
Extreme learning machine<br>
EXALCATE (I-B)<br>
EXALCATE (I-B)<br>
F(x) = Z^R \omega(x) + a<br>
For (j-B)<br>
l(x_j, x_i) = \exp \left[-\delta ||x_j - x_i||^2\right]<br>
If (l-B)<br>
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left(\exp \left[-\deltaFor (i=0)<br>
f(x) = Z^R \omega(x) + \alpha<br>
For (j=0)<br>
l(x_j, x_i) = \exp \left[-\delta ||x_j - x_i||^2\right]<br>
If (l=0)<br>
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} (\exp \left[-\delta \right)<br>
Else (l>0)<br>
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} (\exp \left[-\delta \right)<br>
End if<br>
End for<br>
End for<br>
End for<br>
End for<br>
En
                         t(x_i) = \sum_{j=1}^{M} \sum_{Y_i \in N_i} (\exp \left[-\delta \left\| x_j - x_i \right\|^2)\right]a<br>
\delta ||x_j - x_i||^2<br>
y_i \in N_i \left( \exp \left[ -\delta ||x_j - x_i||^2 \right] \right)<br>
y_i \in N_i \left( \exp \left[ -\delta ||x_j - x_i||^2 \right] \right) = 1\omega(x) + a<br>
\exp \left[-\delta ||x_j - x_i||^2\right]<br>
\sum_{j=1}^{M} \sum_{Y_i \in N_i} \left(\exp \left[-\delta ||x_j - x_i||^2\right]\right)<br>
\sum_{j=1}^{M} \sum_{Y_i \in N_i} \left(\exp \left[-\delta ||x_j - x_i||^2\right]\right) = 1\begin{array}{l} \frac{\mathbf{SVM}}{\mathbf{Input: j, I}} \\\\ \text{Input: j, I} \\\\ \mathbf{Cutput: l, x} \\\\ \mathbf{For (i=0)} \\\ f(x) = Z^R \omega(x) + a \\\\ \mathbf{For (j=0)} \\\ l(x_j, x_i) = \exp \left[-\delta \left\|x_j - x_i\right\|^2\right] \\\\ \text{If (l=0)} \\\ l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left(\exp \left[-\delta \left\|x_j - x_i\right\|\right) \\\\ \text{Else (l>0)} \\\ l(x_j, x_i) = \sum_{j=1}^M \sumInput: J,1<br>
Output: 1, x<br>
For (i=0)<br>
f(x) = Z^R \omega(x) + a<br>
For (j=0)<br>
l(x_j, x_i) = \exp \left[-\delta ||x_j - x_i||^2\right]<br>
If (l=0)<br>
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left(\exp \left[-\delta ||x_j - x_i\right)\right]<br>
Else (l>0)<br>
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left(\exp \left[-\delta ||x_j - x_i\right)\Curput: 1, x<br>
For (i=0)<br>
f(x) = Z^R \omega(x) + \alpha<br>
For (j=0)<br>
l(x_j, x_i) = \exp \left[-\delta ||x_j - x_i||^2\right]<br>
If (l=0)<br>
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left(\exp \left[-\delta ||x_j - x_i\right)\right]<br>
Else (l>0)<br>
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left(\exp \left[-\delta ||x_j - x_i\right)\right]<br>
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 End
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  As shown in algorithm 1, the extreme learning machine<br>
algorithm based on the SVM classifier. ELM's essence consists<br>
of and offer End of the extreme learning machine<br>
algorithm based on the SVM classifier. ELM's essence 
  a<br>
I(x_j, x_i) = \sum_{j=1}^{M} \sum_{Y_i \in N_i} (\exp[-\delta ||x_j - x_i||^2])<br>
Else (1>0)<br>
I(x_j, x_i) = \sum_{j=1}^{M} \sum_{Y_i \in N_i} (\exp[-\delta ||x_j - x_i||^2]) = 1<br>
End for<br>
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End for<br>
End for<br>
As shown in algorithm 1, the extreme learning machine<br>
algorithm based 
  l(x_j, x_i) = \sum_{j=1}^{n} \sum_{Y_i \in N_i} (\exp[-\delta ||x_j - x_i||^2])<br>
Else (1>0)<br>
l(x_j, x_i) = \sum_{j=1}^{M} \sum_{Y_i \in N_i} (\exp[-\delta ||x_j - x_i||^2]) = 1<br>
End if<br>
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End for<br>
As shown in algorithm 1, the extreme learning machine<br>
algorithm based on the
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configuration while analytically evaluating output weights by
the simple generalized inverse operation. ELM, in many cases,
tends to need hidden neurons rather than standard tuning
algorithms. Since the biases and weights Else (1>0)
 $l(x_j, x_i) = \sum_{j=1}^{M} \sum_{Y_i \in N_i} (exp[-\delta ||x_j - x_i||^2]) = 1$

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As shown in algorithm 1, the extreme learning machine

As shown in algorithm based on the SVM classifier. ELM's ess $\mathcal{I}(x_j, x_i) = \sum_{j=1}^{M} \sum_{Y_i \in N_i} (\exp[-\delta ||x_j - x_i||^2]) = 1$

End if

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Return

As shown in algorithm 1, the extreme learning machine

algorithm based on the SVM classifier. ELM's essence consists

of ran Example generalized inverse operation. ELM, in many cases,

End inverse operation. The simple generalized inverse operation will be simple generalized inverse operation. ELM's exerce consists

of randomly assigning the le **End for**
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As shown in algorithm based on the SVM classifier. ELM's essence consists

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algorithm based on the SVM classifier. ELM's essence consists

involving biases and input weights and not requiring

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nages using deep learning techniques (XXXXX)
calculated by purely numerical manipulation, extreme learning
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The SVM algorithm is the basis of the analysis of a supervised learning method, applied to a classification issue in them-class. FIEE ACCESS XXXX: Brain Tumor Identification and Classification of MRI images using deep learning techniques (

of image processing will result in quality degradation. The calculated by purely numeric

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calculated by purely numerical manipulation, extreme learning
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The SVM algorithm is the basis of the analysis calculated by purely numerical manipulation, extreme learning
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The SVM algorithm is the basis of the analysis of a supervised
learning method, applied to a calculated by purely numerical manipulation, extreme learning
machine has low calculation time for training for new classifiers.
The SVM algorithm is the basis of the analysis of a supervised
learning method, applied to a The primary purpose of the SVM algorithm is
nonlinear divisive goal into a linear transformation
feature called the SVM kernel function. The tran
function has been used in the Gaussian kernel. Th
kernel function allows no The SVM algorithm is the basis of the analysis of a supervised
learning method, applied to a classification issue in them-class.
The primary purpose of the SVM algorithm is to turn a
nonlinear divisive goal into a linear learning method, applied to a classification issue in them-class.
The primary purpose of the SVM algorithm is to turn a
nonlinear divisive goal into a linear transformation utilizing a
feature called the SVM kernel functi The primary purpose of the SVM algorithm is to turn a
nonlinear divisive goal into a linear transformation utilizing a
feature called the SVM kerrel function. The transformation
function has been used in the Gaussian kerr nonlinear divisive goal into a linear transformation utilizing a
feature called the SVM kernel function. The transformation
function has been used in the Gaussian kernel. The use of a
kernel function allows nonlinear samp

$$
f(x) = Z^R \omega(x) + a \tag{18}
$$

means and described as "original."
 $MSE = \frac{1}{N \times M} \sum_{N \times M} (f(y,x) - f^T(y,x))^2$ (16) As shown in equation (18)
 Algorithm is equality of the contract on the security of the image reconstruction.
 Algorithm 4.6 Extreme learnin feature called the SVM kernel function. The transformation
function has been used in the Gaussian kernel. The use of a
kernel function allows nonlinear samples to be converted into a
high-dimensional future space where sa function has been used in the Gaussian kernel. The use of a
kernel function allows nonlinear samples to be converted into a
high-dimensional future space where samples data or nonlinear
samples can be isolated or graded. $f(x) = Z^{R}\omega(x) + a$ (

As shown in equation (18) w

parameter and $\omega(x)$ is a function more significant dimensional space

nonlinear SVM Gaussian Kern

Generalization and classification

advanced classification features in
 $= Z^R \omega(x) + a$ (18)

shown in equation (18) where *Z* and *R*, hypotenere and $ω(x)$ is a function utilized to map vector

e significant dimensional space. The equation (19) g

linear SVM Gaussian Kernel function used

era parameter and $\omega(x)$ is a function more significant dimensional space
nonlinear SVM Gaussian Kern
Generalization and classification
advanced classification features in
 $l(x_j, x_i) = \exp \left[-\delta ||x_j - x_i||^2\right]$
 $l(x_j, x_i) = \sum_{j=1}^{M} \sum_{Y$ \vec{x} *i* is a function utilized to map vector x into a dimensional space. The equation (19) gives the Gaussian Kernel function used for the nd classification optimal solution and its cation features in equation (20), $\$ As shown in equation (18) where Z and R, hyperplane
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more significant dimensional space. The equation (19) gives the
nonlinear SVM Gaussian Kernel function As shown in equation (18) where Z and K , hyperplane
parameter and $\omega(x)$ is a function utilized to map vector x into a
more significant dimensional space. The equation (19) gives the
nonlinear SVM Gaussian Kernel func parameter and $\omega(x)$ is a tunction utilized to map vector x into a
more significant dimensional space. The equation (19) gives the
nonlinear SVM Gaussian Kernel function used for the
Generalization and classification opti

$$
l(x_j, x_i) = \exp\left[-\delta \|x_j - x_i\|^2\right] \tag{19}
$$

$$
l(x_j, x_i) = \sum_{j=1}^M \sum_{Y_i \in N_i} \left(\exp\left[-\delta \|x_j - x_i\|^2\right]\right) \tag{20}
$$

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accuracy ground truth, specificity, and sensitivity. Figure 4

accuracy ground truth, specificity, and sensitivity. Figure 4

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shows the Graphical Representation of SVM based ELEACCESS

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separable data. Section 4 illustrates accuracy ground truth, specificity, and sensitivity. Figure 4 segmentation. Only visual is
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\nhaages using deep learning techniques (XXXX) segmentation. Only visual inspection has necessary to determine the accuracy of the segmentation of healthy tissues qualitatively. Dice similarity coefficient is an overlap measure between two images and defined as,

\n
$$
Dice(B, A) = 2 \times \frac{|B_1 \wedge A_1|}{(|B_1| + |A_1|)}
$$
 (21)

mages using deep learning techniques (XXXXX)
segmentation. Only visual inspection has necessary
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Dice similarity coefficient is an overlap measure
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the accuracy of the segmentation of healthy tissues qualitatively.
Dice similarity coefficient is an overlap mea algorigories using deep learning techniques (XXXXX)
segmentation. Only visual inspection has necessary to determine
the accuracy of the segmentation of healthy tissues qualitatively.
Dice similarity coefficient is an over segmentation. Only visual inspection has necessary to determine
the accuracy of the segmentation of healthy tissues qualitatively.
Dice similarity coefficient is an overlap measure between two
images and defined as,
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the accuracy of the segmentation of healthy tissues qualitatively.
Dice similarity coefficient is an overlap measure between two
images and defined as,
 $Dice(B, A$ segmentation. Only visual inspection has necessary to determine
the accuracy of the segmentation of healthy tissues qualitatively.
Dice similarity coefficient is an overlap measure between two
images and defined as,
 $Dice(B, A$ method.

Figure 5: Dice Similarity Coefficient

Table 1 demonstrates the dice similarity coefficient of the $\frac{500}{100} = 50.4$

proposed FAHS-SVM method (Mean and Standard Deviation).

The gross tumor region, including active, ne Figure 5: Dise Similarity Coefficient

Table 1 demonstrates the dice similarity coefficient of the $\frac{500}{100}$ $\frac{50.4}{29}$

proposed FAHS-SVM method (Mean and Standard Deviation). (ii) Segmentation Acc

The gross tumo Figure 5: Dice Similarity Coefficient

Table 1 demonstrates the dice similarity coefficient of the $\frac{500}{100}$ 50.4 29.8

proposed FAHS-SVM method (Mean and Standard Deviation).

The gross tumor region, including active Figure 5: Dice Similarity Coefficient
Table 1 demonstrates the dice similarity coefficient
proposed FAHS-SVM method (Mean and Standard Dev
The gross tumor region, including active, necrotic, and
parts, comprises a gross t proposed FAHS-SVM method (Mean and 3)
The gross tumor region, including active,
parts, comprises a gross tumor volume (GT
provided with and without regularization
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for each sub-r Table 1 demonstrates the dice similarity
proposed FAHS-SVM method (Mean and S
The gross tumor region, including active, n
parts, comprises a gross tumor volume (GTV
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500 | 50.4 | 29.8 | 43.6 | 65.1 | 85.6 | 97.6 |

 SVM \vert \vert DNN \vert SVM \vert \vert \vert readings are evaluated based on texts. features are evaluated based on texture analysis in this review. Figure 6 demonstrates the segmentation accuracy analysis of the suggested FAHS-SVM approaches. Finally, a robust initialization of labeling is created, taking both and high-profile candidate regions incomended, the values of the valu SV and high-profile candidate regions into account. Results of the values of the accuracy of our automated system is similar to the values into account. Results of the accuracy of our automated system is similar to the val $\frac{1}{200}$ $\frac{1}{200}$ $\frac{1}{300}$ $\frac{1}{400}$ $\frac{1}{500}$

Number of Available Dataset
 (ii) Segmentation Accuracy Analysis

The accuracy of our automated system is similar to the values

recorded for manual segmental ²⁰⁰ ³⁰⁰

³⁰⁰ Number of Available Dataset
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 611) Segmentation Accuracy Analysis

The accuracy of our automated system is similar to the values
 Number of Available Dataset

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(ii) Segmentation Accuracy Analysis

The accuracy of our automated system is similar to the values

recorded for manual segmental inter-observer variability. 500 50.4 29.8 43.6 65.1 85.6 97.6
 (ii) Segmentation Accuracy Analysis

The accuracy of our automated system is similar to the values

recorded for manual segmental inter-observer variability.

Finally, a 500 50.4 29.8 43.6 65.1 85.6 97.6

(ii) **Segmentation Accuracy Analysis**

The accuracy of our automated system is similar to the values

recorded for manual segmental inter-observer variability.

Finally, a robust initial $\frac{1}{29.8}$ $\frac{1}{43.6}$ $\frac{1}{65.1}$ $\frac{85.6}{197.6}$

(ii) Segmentation Accuracy Analysis

The accuracy of our automated system is similar to the values

recorded for manual segmental inter-observer variability.

Final $\frac{150.4}{129.8}$ $\frac{129.8}{143.6}$ $\frac{165.1}{185.6}$ $\frac{197.6}{161}$ **Segmentation Accuracy Analysis**
The accuracy of our automated system is similar to the values
recorded for manual segmental inter-observer variability (II) **Segmentation Accuracy Analysis**
The accuracy of our automated system is similar to the values
recorded for manual segmental inter-observer variability.
Finally, a robust initialization of labeling is created, taking The accuracy of our automated system is similar to the values
recorded for manual segmental inter-observer variability.
Finally, a robust initialization of labeling is created, taking both
SVM and high-profile candidate re The accuracy of our automated system is similar to the values
recorded for manual segmental inter-observer variability.
Finally, a robust initialization of labeling is created, taking both
SVM and high-profile candidate re recorded for manual segmental inter-observer variability.

Finally, a robust initialization of labeling is created, taking both

SVM and high-profile candidate regions into account. Results of

the validation experiment on Finally, a robust initialization of labeling is created, taking be SVM and high-profile candidate regions into account. Results the validation experiment on multi-parametric images show that increased accuracy in tumor seg

Figure 6: Segmentation Accuracy Analysis

The super-pixel of the detection of the detection of the probability of the detection

The super-pixel and $\frac{1}{2}$ and $\frac{1}{2}$ and $\frac{1}{2}$ and $\frac{1}{2}$ and $\frac{1}{2}$ and $\$ Figure 6: Segmentation Accuracy Analysis

Figure 6: Segmentation Accuracy Analysis

(iii)Fractal Dimension vs. Mean Intensity

From the binary channels, which involve area intensity and

fractal dimension, the fractal fea Figure 6: Segmentation Accuracy Analysis

Figure 6: Segmentation Accuracy Analysis

(iii)Fractal Dimension vs. Mean Intensity

From the binary channels, which involve area intensity and

fractal dimension, the fractal fea Figure 6: Segmentation Accuracy Analysis

(iii) Fractal Dimension vs. Mean Intensity

From the binary channels, which involve area intensity and

fractal dimension, the fractal features are measured. The feature

area is binary channers, which
mension, the fractal feature
e super-pixel number of edge
pective to edge pixels in
of the images. The fract
of the images are fraction of $\frac{\log M(\varepsilon)}{\log \varepsilon^{-1}}$ (22)
in equation (22), where *M*
ubes exper-pixel number of edge pixels. Therefore, in a super-pixel number of edge pixels. Therefore to edge pixels in a super-pixe of the images. The fractal dimension of the image structure and is measured as $\frac{\log M(\varepsilon)}{\log \v$ Figure 6. Segmentation Accuracy Anaysis

(iii)Fractal Dimension vs. Mean Intensity

From the binary channels, which involve area intensity and

fractal dimension, the fractal features are measured. The fracture

pixels re (iii)Fractal Dimension vs. Mean Intensity

From the binary channels, which involve area intensity and

fractal dimension, the fractal features are measured. The feature

area is the super-pixel number of edge pixels. The From the binary channels, which involve area intensity and

fractal dimension, the fractal features are measured. The fracture

pixels respective to edge pixels in a super-pixel is the mean

intensity of the images. The f From the binary channels, which involve area intensity and

fractal dimension, the fractal features are measured. The feature

area is the super-pixel number of edge pixels. The intensity of

intensity of the images. The fractal dimension, the fractal features are measured. The feature

area is the super-pixel number of edge pixels. The intensity of

pixels respective to edge pixels in a super-pixel is the mean

difficulty of the images.

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C_0 = \lim_{E \to 0} \frac{\log M(\varepsilon)}{\log \varepsilon^{-1}} \tag{22}
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A broad range of features such as intensity textures, label

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A broad range of features such as intensity textures, label
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lengths, spatial tissue prior probabilities, ar
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on the nature of the issue. Based on trair
complex classification outcome and
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Tigure 8: Probability of Detection Ratio

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Table 2 demonstrates the probability of detection ratio

evaluation of the suggested FAHS-SVM method. The

probabilistic neural network cl Tigure 8: Probability of Detection Ratio

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Table 2 demonstrates the probability of detection ratio

evaluation of the suggested FAHS-SVM method. The

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evaluation of the suggested FAHS-SVM method. The

probabilistic neural network classifier has been employed to

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evaluation of the suggested FAHS-SVM method. The

probabilistic neural network classifier has been employed to

train and evaluation of the suggested FAHS-SVM methorous
probabilistic neural network classifier has been emp
train and test for tumor accuracy in brain MRI image
tumor detection at a very early stage has a crucial issu
proper ther Table 2 demonstrates the probability evaluation of the suggested FAHS-SV
probabilistic neural network classifier has
train and test for tumor accuracy in brain 1
tumor detection at a very early stage has a c
proper therapy

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(v) Classification Error our automated approach is

Tumor size affects the accuracy of segmentation, and tumor

fo boundaries are usual errors. Large brain under MRI images using deep learning techniques (XX
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(v) Classification Error our automated approach is segmentation inter-observer

Tumor size affects the accu **ICCLESS** XXXX: Brain Tumor Identification and Classification of MRI images using deep learning techniques

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regmentation inter-observer v

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bigh number of misclassified image pixels. Furthermore, large

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beyondaries are usual errors. Large brain tumors are defined by a

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boundaries are usual errors. Large brain tumors are defined by a
statistical classification high number of misclassified image pixels. Furthermore, large
are spati Fumor size affects the accuracy of segmentation
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high number of misclassified image pixels. Furthe
tumors probably enter the brain and CSF a
challenging to determine the

Example the set of tunority of the control of the control of the control of the control of tumors and normal.
 between pixels of tumor and of tumority and system
 between pixels of tumor and normal. Finally, the new 1. Mohsen, H., El-Dahsh

ab B. M. (2018). Classification

in tumors. Future

in tumors. Future

The extraction phase features calculate an intensity and system

The extraction phase features calculate an intensity and syst The extraction **Example 10**

100 $\frac{1}{200}$ $\frac{1}{300}$ $\frac{1}{400}$ $\frac{1}{500}$ $\frac{1}{500}$

11. Sumber of Datasets

Figure 9: **Classification Error**

The extraction phase features calculate an intensity and system

The **Example the technique takes into account not only local tumor images.** *Frage S*
 Example 50
 Example 50
 Example 10
 Examplement Properties such as gradients and region length. Although the FAHS-SVM has relatively such as the size of the si Figure 9: **Classification Error**

Figure 9: **Classification Error**

The extraction phase features calculate an intensity and system and the computer of the extractized vector for each pixel. Subsequently, SVM

characterize Figure 9: **Classification Error**
 accuracy accuracy action Exerce in the set and system

The extraction phase features calculate an intensity and system

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characterized vector for each pixel. Sub Figure 9: **Classification Erro

The extraction phase features calculate an intensity and system**

The extraction phase features calculate an intensity and system

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characterized vector for each pixel. Figure 9: Classification Error

The extraction phase features calculate an intensity and system

The extracterized vector for each pixel. Subsequently, SVM

characterized vector for each pixel. Subsequently, SVM

develops The extraction phase features calculate an intensity and system

characterized vector for each pixel. Subsequently, SVM

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develops a classification model providing the distin The extraction phase leadures calculate an intensity and system

characterized vector for each pixel. Subsequently, SVM

develops a classification model providing the distinction

between pixels of tumors and normal. Fina accuracy. are classified to extract tumor areas (i.e., the
The method FAHS-SVM in brain tumor seg
because the technique takes into account no
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because the technique takes into account not only local tumor
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properties such as gradients and global aspects such as the size

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of thuson, S. Anwar, S. M.

accuracy achieved and has been high relative to other

accuracy achieved and has been high relative to other

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S. Conclusion

S. Conclusion with extensive data augmentation. Journal of computation

This paper presents a Fully Automatic Heterogeneous

Segmentation sing Support Vector Machine (FAHS-SVM) for

VOLUME XX, 2019

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regions by combining intrinsic image structure hierarchy and
statistical classification information. The tumor areas described
are spatially small and consistent c regions by combining intrinsic image structure nerarcry and
statistical classification information. The tumor areas described
are spatially small and consistent concerning image content and
provide an appropriate and robus statistical classification information. The tumor areas described
are spatially small and consistent concerning image content and
provide an appropriate and robust guide for the consequent
segmentation. The proposed method are spatially small and consistent concerning image content and
provide an appropriate and robust guide for the consequent
exgementation. The proposed method can achieve promising
tumor segmentation in conjunction with a s provide an appropriate and robust guide for the consequent
segmentation. The proposed method can achieve promising
tumor segmentation in conjunction with a semi-supervised
approach under a local and globalized accuracy sys segmentation. The proposed method can achieve pro
tumor segmentation in conjunction with a semi-supe
approach under a local and globalized accuracy system
shown by experiments focused on multi-parametric Ma
Resonance image Resonance images. Our experimental results indicate that the
method proposed will help to identify the exact location of the
brain tumor accurately and quickly. The proposed method is,
therefore, critical for MR imagery br method proposed will help to identify the exact location of the brain tumor accurately and quickly. The proposed method is, therefore, critical for MR imagery brain tumor detection. The experimental results showed 98.51% o

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