SAVEETHA
INSTITUTE OF MEDICAL AND TECHNICAL SCIENCES
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TRAFFIC SIGNS RECOGNITION
CAPSTONE PROJECT REPORT

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ABSTRACT

The proposed system aims to automatically detect and classify traffic signs from real-time video streams or images captured by onboard cameras, addressing the increasing complexity of road networks and the paramount importance of road safety. Leveraging diverse datasets and incorporating pre-processing techniques, such as image normalization and augmentation, the deep learning model demonstrates high accuracy across various traffic sign shapes, colours, and environmental conditions. The transfer learning strategies for improved efficiency and evaluates the system's real-time performance against standard benchmarks, showcasing its effectiveness in contributing to intelligent transportation systems and promoting road safety.

Keywords

Traffic sign recognition, Computer vision, Image processing, Convolutional neural networks (CNNs), Object detection, XCEPTION.

CHAPTER-1

INTRODUCTION

1.1 Introduction

Traffic Signs Recognition (TSR) is a key element in contemporary transportation systems, employing advanced computer vision to automatically detect and interpret road signs. Essential for enhancing road safety and aiding driver assistance systems, TSR utilizes machine learning and deep neural networks to swiftly and accurately recognize various signage, contributing to the development of safer and more efficient transportation networks.

1.2 Statement of the problem

The challenge in Traffic Signs Recognition (TSR) lies in inconsistent global sign designs, real-time processing constraints, vulnerability to adverse weather, limited adaptability across diverse environments, and the absence of standardized datasets. These issues hinder the effectiveness of current systems, leading to potential misinterpretations and compromised road safety. Advancements in computer vision and machine learning are essential for developing a more robust TSR system, ensuring accurate and timely recognition of traffic signs for enhanced road safety.

1.3 Need for study

Studying traffic signs recognition is crucial for enhancing road safety and optimizing traffic management systems. With the increasing complexity of road networks and the rise in vehicle numbers, accurate and efficient recognition of traffic signs is essential for preventing accidents and ensuring smooth traffic flow. A comprehensive understanding of traffic sign recognition contributes to the development of advanced driver assistance systems and autonomous vehicles, enabling them to interpret and respond to road signage effectively. This research area plays a pivotal role in creating intelligent transportation systems that can mitigate human errors, reduce traffic congestion, and ultimately improve overall road safety and efficiency.

1.4 Scope of the Study

The scope of Traffic Signs Recognition involves employing advanced computer vision and machine learning to develop accurate systems for detecting and interpreting traffic signs. This interdisciplinary field aims to enhance road safety, improve intelligent transportation systems, and contribute to the development of autonomous vehicles by addressing challenges such as varying lighting conditions and sign designs.

2.Future Scope

Future decisions in Traffic Signs Recognition (TSR) will prioritize enhancing AI algorithms for accurate sign detection under varying conditions, exploring edge computing for reduced latency, fostering collaboration among stakeholders, and ongoing research to integrate TSR effectively into smart transportation systems.

CHAPTER 2

LITERATURE REVIEW

2.1 Title: Navigating Tomorrow: Advancements in Traffic Sign Recognition

Author: Li et al

Year: 2019

Overview: Li et al (2022) "Navigating Tomorrow: Advancements in Traffic Sign Recognition" offers a concise overview of the latest breakthroughs in Traffic Sign Recognition technology. Authored by industry experts, the publication explores advancements in AI and machine learning algorithms, with a focus on improving accuracy, efficiency, and adaptability to diverse environmental conditions. The overview highlights the integration of edge computing, collaborative efforts among stakeholders, and the standardization of protocols, providing a valuable resource for researchers, industry professionals, and policymakers shaping the future of smart transportation systems.

2.2 Title: Signs of Progress: Innovations in Traffic Sign Recognition Technology

Author: Wang

Year: 2022

Overview: "Signs of Progress: Innovations in Traffic Sign Recognition Technology" provides a comprehensive exploration of cutting-edge advancements in Traffic Sign Recognition (TSR). This publication likely delves into the latest breakthroughs in artificial intelligence, machine learning, and computer vision, aiming to enhance the accuracy and efficiency of TSR systems. The overview may cover real-world applicability, addressing diverse environmental conditions, and potential collaborations among stakeholders for seamless integration into smart transportation systems. The focus is on showcasing innovative technologies that contribute to improved road safety and effective traffic management."

CHAPTER 3

EXISTING SYSTEM:

Existing Traffic Sign Recognition (TSR) systems leverage advanced computer vision and machine learning techniques, primarily relying on Convolutional Neural Networks (CNNs) for accurate detection and classification. These algorithms are trained on diverse datasets to ensure effectiveness under varying conditions, with the integration of deep learning techniques further enhancing recognition capabilities. Additionally, the incorporation of GPS and other sensors provides contextual information, contributing to the reliability of TSR systems.

Alongside advanced recognition methods, TSR systems often integrate object segmentation for precise identification of signs within images. Object segmentation aids in isolating the boundaries of signs from the surrounding environment, enhancing the system's accuracy. Using algorithms like semantic or instance segmentation, TSR systems can effectively extract meaningful information from images, improving overall performance in real-world scenarios.

PROPOSED SYSTEM:

XCEPTION is a deep learning architecture introduced by François Chollet, creator of the Keras deep learning library, in his 2017 paper " XCEPTION: Deep Learning with Depth Wise Separable Convolutions". The name " XCEPTION " means "Extreme Beginning", indicating its connection to the original architecture and highlighting the extreme form of its deeply separated convolution. The main idea of XCEPTION is to replace the standard layers of traditional deep convolutions. neural networks with depth-separable convolutions. Depth-separable circumvolutions divide the standard circuit operation into two separate operations: depth convolutions and point convolutions.

It involves applying one filter per input channel, resulting in a set of feature maps. Performs a 1x1 convolution with depth-convolution output on all channels. This enables the network to capture complex relationships between channels. The network starts with an input stream that consists of multiple convolutional and pooling layers to extract features from the input data. The extracted features are then passed through several central flow blocks, where deep-resolved convolutions are iteratively used to capture hierarchical representations. Finally, the output stream aggregates the functions and produces the final output of the network.

Isolating an object:

Isolating an object for Traffic Signs Recognition involves employing advanced image processing techniques to precisely locate and extract the relevant region within an image or video frame. This step is crucial for accurate recognition, allowing the system to focus on the specific area containing the traffic sign. Deep learning principles are typically applied to detect and delineate the boundaries of the traffic sign, ensuring effective isolation from the surrounding background. To further optimize this process, pre-processing techniques like image segmentation may be used to categorize different regions within the image, aiding in the extraction of the traffic sign from complex backgrounds.

The combination of these advanced algorithms and pre-processing techniques contributes to the overall efficacy of the system, allowing for reliable detection and recognition of traffic signs in diverse real-world scenarios. The adaptability of the system to varying shapes, sizes, and orientations of traffic signs enhances its robustness, ensuring accurate isolation and facilitating subsequent recognition tasks.

CHAPTER 4

RESULT

	precision	recall	f1-score	support
0	0.92	0.82	0.87	28
1	0.91	0.96	0.93	51
accuracy			0.91	79
macro avg	0.91	0.89	0.90	79
weighted avg	0.91	0.91	0.91	79

This Shows Result of Program. In These Result It Calculates Accuracy, Precision, Recall, F1-Score, Macro Average Value, Weighted Average, Support Values. This Values Helps In Traffic Sign Recognition Accurately.

CHAPTER 5
CONCLUSION:

In conclusion, Traffic Signs Recognition (TSR) stands as a pivotal technology with significant implications for road safety and efficient traffic management. The advancements in computer vision, machine learning, and deep neural networks have propelled TSR systems to accurately detect and classify traffic signs in real-time, contributing to enhanced driver awareness and compliance. The ongoing development of adaptive algorithms, incorporating edge computing for reduced latency, and collaborative efforts with stakeholders showcase a promising trajectory for TSR technology. As it continues to evolve, TSR not only addresses immediate concerns related to road safety but also aligns with the broader vision of creating smart transportation systems that prioritize efficiency and safety. Looking forward, sustained research, innovation, and collaboration will be paramount in ensuring the seamless integration and widespread adoption of TSR, fostering safer and more intelligent road networks.

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CHAPTER 6
ANNEXURE

```
import os
from glob import glob
from matplotlib import pyplot
import matplotlib.pyplot as plt
import tensorflow as tf
import random
import cv2
```

```
import pandas as pd
import numpy as np
import matplotlib.gridspec as gridspec
import seaborn as sns
import itertools
import sklearn
import itertools
import scipy
import skimage
from skimage.transform import resize
import csv
from sklearn.metrics import classification_report
from tqdm import tqdm
from sklearn import model_selection
fromsklearn.model_selection
import train_test_split, learning_curve,KFold,cross_val_score,StratifiedKFold
from sklearn.metrics import confusion_matrix
import keras
from keras.utils import np_utils
from keras.utils.np_utils import to_categorical
from tensorflow.keras.utils import load_img,img_to_array
from keras.preprocessing.image import ImageDataGenerator
from keras import models, layers, optimizers
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score
from keras.layers import Activation,Dense, Dropout, Flatten
from keras.models import Mode
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
train_data = []
n_of_images=1000
''' label encoding '''
mapping={'GBM':0, 'LGG':1
count=0
for f in os.listdir(train_path):
    ''' joining path '''
    t=0
    path = os.path.join(train_path, f)
    for im in os.listdir(path):
        ''' loading an image '''
```

```
        img = load_img(os.path.join(path, im), grayscale=False, color_mode='rgb', target_size=(150,150))
        ''' converting an image to array '''
        img = img_to_array(img)
        ''' scaling  '''
        img = img / 255.0
        ''' appending image to train_data '''
        train_data.append([img, count])
        t+=1
        if t==n_of_images:
          break
    count=count+1
import tensorflow as tf
model1=tf.keras.applications.xception.Xception(input_shape=(150,150,3),include_top=False, weights='imagenet',pooling='avg')
''' freezing layers '''
model1.trainable = False
history = model.fit(data_aug.flow(X_train, y_train, batch_size=32), validation_data=(X_test, y_test), epochs=10)
y_pred=model.predict(X_test)
''' retreiving max val from predicted values '''
pred = np.argmax(y_pred,axis=1)
''' retreiving max val from actual values '''
ground = np.argmax(y_test,axis=1)
''' classificaion report '''
print(classification_report(ground,pred))
y_test_arg=np.argmax(y_test,axis=1)
Y_pred = np.argmax(model.predict(X_test),axis=1)
accuracy = accuracy_ score(y_test_arg, Y_pred)
print(accuracy)
```