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USE OF ARTIFICIAL INTELLIGENCE IN ROAD TRAFFIC AND PAVEMENT ENGINEERING.

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ABSTRACT
This study examines the many uses of artificial intelligence (AI) in pavement engineering and road traffic management. The monitoring, management, and optimization of transportation networks are being completely transformed by AI technologies, which will increase sustainability, efficiency, and safety. AI systems are used in road traffic management to help with accident detection and management, traffic pattern prediction, and traffic signal timing optimization. These solutions increase overall road safety, improve traffic flow, and lessen congestion. Furthermore, artificial intelligence (AI) makes it easier to forecast pavement deterioration, evaluate pavement conditions, and optimize maintenance plans by evaluating a variety of data sources. Moreover, AI-driven pavement design and construction methods result in more durable and economical pavements. Environmental factors are also taken into account; for example, AI is used to create eco-friendly pavement and optimize traffic flow to cut emissions.
In order to create a model for picture classification with high accuracy and compare it to previous studies, we used AI-powered algorithms in our research. The Bhubaneswar Traffic Sign Benchmark dataset was utilized to build the Convolutional Neural Network (CNN), to which we incorporated several features of our own to increase accuracy. We examine the accuracy and loss numbers and compare the performances with each epoch while we train our model for a certain number of epochs. Our model improves through forward and back propagation throughout the training phase. Our model's ultimate objective is to be sufficiently trained to identify characteristics, allowing us to get a respectably high accuracy rate. We contrast our findings.
KEY WARDS-Artificial intelligence (AI), Convolutional Neural Network (CNN), pavement engineering traffic management, eco-friendly pavement

INTRODUCTION-
Artificial Intelligence (AI) refers to the simulation of human intelligence processes by machines, especially computer systems. It involves the development of algorithms and models that enable computers to perform tasks typically requiring human intelligence. AI encompasses a wide range of techniques, including machine learning, deep learning, natural language processing, computer vision, and robotics, among others. These techniques enable AI systems to perceive their environment, learn from data or experiences, reason about situations, and make decisions or take actions to achieve specific goals. AI has numerous applications across various fields, such as healthcare, finance, transportation, education, and entertainment, and it continues to advance rapidly, driving innovations and transforming industries. Within the field of civil engineering, pavement engineering deals with the planning, building, upkeep, and repair of pavement constructions, mainly for use on highways, airports, and other forms of transportation infrastructure. Creating long-lasting, secure, and economically viable pavement systems that can endure traffic volumes and environmental conditions is the main objective of pavement engineering. Road traffic refers to the movement of vehicles, pedestrians, and other users on public roads or highways. It encompasses all activities related to the transportation of people and goods via roadways, including vehicular traffic, pedestrian traffic, and interactions between various road users.
In this study, we have developed and evaluated an application for road sign detection using the well-

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known CNN (Convolutional Neural Network) neural network for picture classification. Until we implement our model into a functional application, we keep developing it via all the phases and procedures. We choose a research where SVM was used for the same goal and compare the findings, continuing to compare our results to other image classification algorithms from other studies since we got high accuracy results. They obtained a training accuracy of 98.33% using the SVM approach, and we obtained a training accuracy of 98.98% and a testing accuracy of 96% using the CNN method. Both approaches seem to be quite successful in resolving this particular issue with a slight difference in result.
The following were the goals of this study:
- Examine several artificial intelligence instruments that may be employed to simulate the deterioration of asphalt pavement performance.
- Create artificial intelligence models to forecast pavement performance metrics based on traffic, environmental, and structural data.

SOFTWAREENVIRONMENT
Forthisexperimentalapproachthesoftwareenvironmentusedis as described below:
Programminglanguage:Python
Environment: Anaconda - Spyder (Python 3.7)Libraries used:
import numpy as np
importpandasaspd
importmatplotlib.pyplotasplt
import cv2
import os
import tensorflow as tf
fromPILimportImage
fromsklearn.model_selection importtrain_test_split
fromkeras.utils import to_categorical
fromkeras.modelsimportSequential,load_model
fromkeras.layersimportConv2D,MaxPool2D,Dense,
Flatten,Dropout
fromsklearn.metricsimportaccuracy_score
import tkinter as tk
from tkinter import filedialog
*from tkinter import **
from PIL import ImageTk, Image
importnumpy
Operating System: Window

LITERATURE REVIEW-
The objective of this task was to conduct a comprehensive literature review of different types of artificial intelligence and their applications in civil and pavement engineering. The main subjects of the literature review were as follows:
• Different measures of pavement deterioration and how they are related to pavement management
• Various artificial intelligence methods and how those methods operate
• Applications of different artificial intelligence models in pavement engineering
• Applications of different artificial intelligence models in civil engineering.
The idea of traffic sign recognition, or TSR for short, is quite straightforward and beneficial to a large number of people. When driving somewhere you're unfamiliar with or you're not familiar with the signs around you, your automobile can help you recognize them more quickly and accurately (Bahlmann, C., Zhu, Y., Ramesh, V., Pellkofer, M., & Koehler, T., 2008). This method provides us

with a safety net to fall back on while driving in unfamiliar places or even allowing the car to drive itself, but it requires the vehicle to comprehend traffic signs in order to do so (Lim K, Hong Y, Choi Y, Byun H, 2017).

Fig.1. Example of a solved TSR problem (Ingram, A, 2015.)

CONSTRUCTING AND EXAMINING A TRAFFIC SIGN RECOGNITION APP –

We'll walk through the procedures required to complete an application that integrates a CNN model that has been trained to assist us classify traffic signs appropriately. The outcomes will be contrasted with an application that uses the SVM technique.
We will use the following procedures to complete this project's construction:
Step 1: examine the dataset.
Step 2: Accuracy and model construction
Step 3: Analysis of the findings
Step 4: Applying the model to an application

Examining the dataset-

Analyzing the dataset that we will be using is how we start our first step. The Bhubaneswar Traffic Sign Benchmark (Institut für Neuroinformatik. (n.d.)., 2013) is a multi-class, single-image data collection tool with around 51,900 files, as required by our project. In total, there are almost 50,000 photos in 43 classes. Examining in more detail, we see that the data collection provides us with Train and Test csv files, which we will utilize to get the desired outcomes.

The following attributes are utilized on the dataset:
- Width (image width) - Height (image height)
- ROI.X1 (the image's upper left X coordinate for the sign)
- Roi.Y1 (the image's upper left Y coordinate for the sign)
- Roi.X2, the sign's lower left X coordinate
-ClassId (class of provided image)
-Path (path to provided image)

Model building and accuracy

The Deep Neural Network model (Bishop, P. o. N. C. C. M., & Bishop, C. M., 1995) is the model that we will be developing for this project. It can classify images, in our case signs, into the appropriate category. In order to solve the problem mentioned above, our suggested solution was to develop a system that can automatically detect and display signs to our driver. The libraries and packages that were listed in the paper's first chapter must be used in order to train our model. Next, we proceed to construct our blank lists, which will house our information, labels, and classification goals. To obtain the

```
- val_loss: 0.6911 - val_accuracy: 0.8238
- val_loss: 0.2516 - val_accuracy: 0.9412
- val_loss: 0.1710 - val_accuracy: 0.9593
- val_loss: 0.1531 - val_accuracy: 0.9623
- val_loss: 0.1099 - val_accuracy: 0.9736
- val_loss: 0.0943 - val_accuracy: 0.9718
- val_loss: 0.0811 - val_accuracy: 0.9784
- val_loss: 0.0817 - val_accuracy: 0.9810
- val_loss: 0.0588 - val_accuracy: 0.9837
- val_loss: 0.0634 - val_accuracy: 0.9855
- val_loss: 0.0748 - val_accuracy: 0.9832
- val_loss: 0.0587 - val_accuracy: 0.9832
- val_loss: 0.0512 - val_accuracy: 0.9861
- val_loss: 0.0626 - val_accuracy: 0.9834
- val_loss: 0.0379 - val_accuracy: 0.9898
```

Fig.2. Output after training our CNN model for 15 epochs

RESULTS AND DISCUSSION

Within the context of this study, we have examined how the CNN and SVM models stack up against one another for this particular use case.

Beginning with the CNN model, we can observe the improvement after each training epoch. The accuracy is shown to be at 0.4 in the first epoch, increasing to 0.7 in the second, and so on. We chose to end our training process after 15 epochs because we didn't notice any improvement in the previous three epochs. To enhance our observation, we can examine the plot displayed in Figure 4.

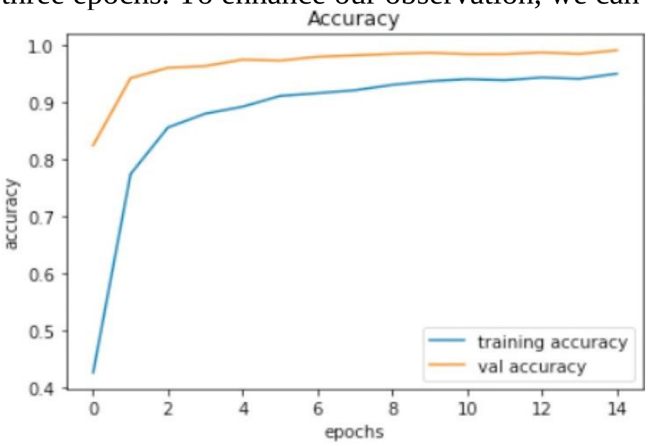

Fig.4.Accuracyvalueaftereach epochwhile training our CNN

Additionally, we can see the loss, indicating that the value fell short of the forecast. We can see that the first epoch loss is at 2.2 in the plot displayed in Fig. 5 and that it gets less with each repetition. We can see the movement of loss with each epoch for better observation, and since it is getting smaller, we can say that our model is getting better.

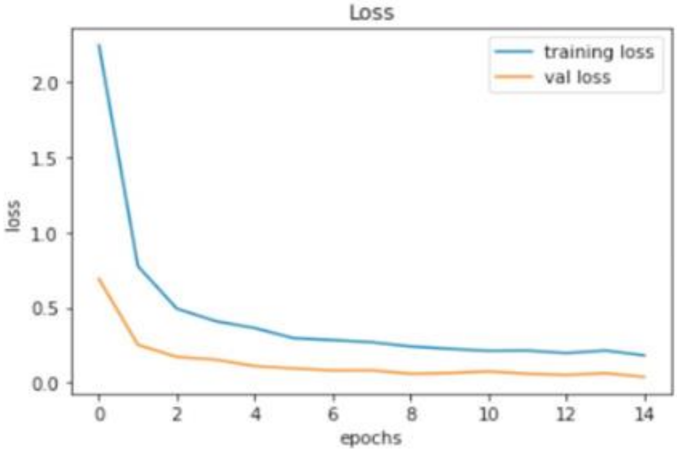

Fig.5.LossvalueaftereachepochwhiletrainingourCNN

We use the test dataset that we separated previously to continue testing our built model, applying the same reasoning (by shrinking and converting from lists to arrays) that we used for the training dataset. To determine whether our model has a high enough accuracy rate to be applied to an application, we use the accuracy ratings obtained by sklearn to calculate our prediction rate. Following testing, we receive an accuracy score of 0.96, or 96%, as indicated in Fig. 6.

Fig.6. Testing accuracy score of our trained model

We proceed to compare our project with another solution after constructing it and evaluating its correctness using the CNN model. We used this work (Hasan, Nazmul & Anzum, Tanvir & Jahan, Nusrat, 2020) as a comparison, in which the SVM model is employed to try and achieve the same application. To determine how these two approaches compare to one another, we have compared the outcomes of both of these strategies.

SVM is a well-known algorithm for problems involving regression and classification. This kind of algorithm separates the data into the required classes precisely by creating hyperlanes between two classes to distinguish them from one another. We need to be aware of the area of interest's "ROI" module in order to apply SVM. There are three distinct phases in this region. Color transfer, which reduces color images to a single color, is the initial phase. The photos are inspected in the second stage, and the ROI is performed in the third to improve the color and shape of the sign so that the car can recognize it more easily (Hasan, Nazmul & Anzum, Tanvir & Jahan, Nusrat, 2020).

As previously indicated, an SVM is used in the study to assess the outcomes instantly. The detection portion makes use of an image processing algorithm that discovers all the circles between each contour created in a frame. With a data sharing ratio of 80:22, the SVM algorithm produced 98.33% training accuracy for traffic sign recognition, but the CNN approach produced 98.98% training accuracy and 96% testing accuracy.

```
Spliting data into training (80%) and test set (20%)...
Training SVM model ...
[10.  8.  2.  9.  2.  6. 11.  2.  9.  8.  4.  2.  5.  0.  3.  7.  2.  0.
  9.  3.  5.  2.  1. 10.  6.  2. 11. 11.  7.  9.  6.  7.  9. 11.  1.  7.
  8.  2.  0.  6.  5. 11. 10.  9.  1.  4.  2.  9.  5. 11.  3.  8.  3.  4.
  4.  5.  8.  3. 10. 11.  9.  1.  5. 10.  2.  3.  3.  6.  5.  4.  8.  3.
  9.  1.  4.  3.  4.  0. 10.  0. 11. 11.  4.  5. 11.  7.  8.  3.  0.  8.
  3.  0.  1.  6.  9.  3.  2. 11.  4. 11.  6.  9.  2.  1.  3.  3. 10.  1.
  9.  0.  1.  7.  1.  3.  5.  5.  7.  5.  9. 10.  4.  9.  8.  4.  3.  6.
  3.  6.  7.  6.  9.  4. 10.  5. 11.  9.  3.  4. 10.  5.  7.  4.  3.  2.
  6.  1. 10.  4.  2.  2.  0. 10.  4. 11.  9. 10.  6.  7. 11. 10.  7.  5.
  9.  6.  7.  5.  8.  8.  7.  3.  7.  2.  3.  1.  0.  4.  7.  7.  6.  6.
  7.  5.  1. 10.  6.  8.  7.  3.  2.  0.  0.  6.  0.  4.  7.  8.  7.  7.
 10.  6.  0. 10. 11.  7.  6.  9.  4. 11.  0.  2.  8.  5.  6.  0.  6.  6.
  4.  7.  0.  0. 10.  9.  4. 11.  0.  3.  2.  3.  3.  5.  0.  4.  2. 10.
 10.  7. 11. 11.  5. 11.]
Accuracy: 98.33 %
```

Fig.7. Output of SVM model (Hasan, Nazmul & Anzum, Tanvir & Jahan, Nusrat, 2020)

Model deployment to an application-

We kept deploying our trained model to a Python desktop application in order to facilitate model testing. We select an image for categorization using a straightforward Graphical User Interface, and then we forecast the sign on the image. As can be seen in Fig. 8, we map the value that will be displayed for each prediction—which is returned to us between 0 and 42—with a more comprehensible description.

Fig.8. Using our built Desktop Application for testing our model.

By choosing the "Select a Photo" button, we choose an image that the model has never seen before. Next, we click the "Predict the Traffic Sign" button, and the output/target is displayed as shown in Figure 9. We keep trying new things with our work, and every time we manually tested the model, it turned out to be accurate.

Fig.9. Case Testing our model

CONCLUSION

- From the above result it was found that in this python programming with AI-powered algorithms to create a highly accurate image categorization model and compare it to previous research.
- Our CNN approach and the SVM approach both show great efficacy in resolving this particular issue, albeit with slightly different outcomes.

REFERENCES -

1. *Mikels N, Kassem E, Muftah A, and Sufian A(2023) The Use of Artificial Intelligence in Pavement Engineering.*
2. *Vesa M. Morina. Greta M. Ahma(2022)Building and Comparing AI-Powered Algorithms in Road Sign Detection*
3. *Arshadi, A., and Kachwalla, A. (2021). Development of a Machine Learning-Based Quality Control Approach for Automated Pavement Condition Data. Reading.*
4. *Artificial Intelligence (AI) vs. Machine Learning, 2022 Bayomy, F., A. Muftah, and E. Kassem. Calibration of the AASHTOWare Pavement ME Design Performance Models for Flexible Pavements in Idaho. Publication FHWA-ID-18-235, ITD Report RP 235, Idaho Transportation Department, 2018.*
5. *Bianchini, A., and Bandini, P. (2010). Prediction of pavement performance through neuro-Fuzzy Reasoning. Computer-Aided Civil and Infrastructure Engineering, 25(1), 39–54. https://doi.org/10.1111/j.1467-8667.2009.00615.x*
6. *Bishop, C. M. (1994). Neural networks and their applications. Review of Scientific Instruments, 65(6), 1803–1832. https://doi.org/10.1063/1.1144830*
7. *Chen, X., Dong, Q., Zhu, H., and Huang, B. (2016). Development of distress condition index of asphalt pavements using LTPP data through structural equation modeling. Transportation Research Part C: Emerging Technologies, 68, 58–69. https://doi.org/10.1016/j.trc.2016.03.011*
8. *Columbia Engineering. (2022, March 3). Artificial Intelligence (AI) vs. Machine Learning. CU-CAI. Retrieved November 8, 2022, from https://ai.engineering.columbia.edu/ai-vs-machine-learning/*
9. *Deng, Y., Luo, X., Zhang, Y., Cai, S., Huang, K., Shi, X., and Lytton, R. L. (2020, November 22). Determination of flexible pavement deterioration conditions using long-term Pavement performance database and artificial intelligence-based finite element model updating. Wiley Online Library. Retrieved October 12, 2021, from https://onlinelibrary.wiley.com/doi/full/10.1002/stc.2671*
10. *Dick, S. (2019). Artificial Intelligence. Issue 1. https://doi.org/10.1162/99608*
11. *Bahlmann, C., Zhu, Y., Ramesh, V., Pellkofer, M., & Koehler, T., 2008. A System for Traffic Sign Detection, Tracking, and Recognition Using Color, Shape, and Motion Information..s.l.:CiteSeerX.*
12. *Lim K, Hong Y, Choi Y, Byun H, 2017. Real-time traffic sign recognition based on a general purpose GPU and deep-learning..s.l.:PLoS ONE.*
13. *Habibi Aghdam, H., & Jahani Heravi, E. , 2017. Guide to Convolutional Neural Networks: A Practical Application to Traffic-Sign Detection and Classification..s.l.:Springer International Publishing.*
14. *Hasan, Nazmul & Anzum, Tanvir & Jahan, Nusrat, 2020. Traffic Sign Recognition System (TSRS): SVM and Convolutional Neural Network..s.l.:ResearchGate.*