Weather Aware Traffic Sign Recognition System

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***Abstract*—The functioning of autonomous vehicles faces immense challenges due to adverse weather conditions dramatically decreasing the precision and dependability of traffic sign recognition systems. While most computer vision models operate exclusively on a visual input, this research develops a mixed model that combines OpenWeatherMap API's real-time weather data—temperature and humidity—with the GTSRB dataset's visual data. Concrete-cutting, deep learning structures that implement image processing of the weather data through Convolutional Neural Networks (CNN) and Dense Neural Networks (DNN) are created. Image datasets underwent augmentation alongside simulation of real-world conditions like the addition of synthetic weather effects—fog, rain, and glare—to transform images into actual conditions. After cleansing, cropping, and applying further refinement processes which included region of interest extraction, normalization, and class balancing, the dataset consists of 39,209 images across 43 distinct classes. The classification model achieves an accuracy of 99.3%, with real-time performance measurement exceeding 100 FPS at a 4 batch size and sustained value during multi-threaded latency-insensitive benchmark testing. The robustness of the system was validated through exhaustive performance assessments including confusion matrices, sample prediction tests, and classification report analysis. Final model validation underwent exportation and unsupervised data testing while architectural analysis simultaneously benchmarked real-time deployability. With this paper, we propose a practical and scalable weather-aware traffic sign recognition system which improves autonomous navigation safety.**

***Index Terms*—Traffic Sign Recognition (TSR), Deep Learning, Weather Adaptation, CNN, DNN, Computer Vision, YOLO, OpenCV, Real-Time Detection, Autonomous Driving, Dataset Augmentation, Smart Transportation Systems.**

I. Introduction and Statement of the Problem

The factors TSR relies on heavily have recently changed. Autonomous vehicles (AVs) have laid the foundation for intelligent transport systems, giving rise to ever growing potential for TSR. Additionally, TSR has now become an essential component of vehicle safety and legal requirements. In simpler terms, TSR helps Autonomous Vehicles to monitor and interpret road signs so that decisions such as, "increase speed?", "stop?" and or "surrender?" can be made accordingly. As of now, most TSR systems make use of cameras installed within the vehicle, using CNNs to decode and classify the information into data the system can make use of.

Image quality is one of the greatest shortcomings when it comes to the environment. Driving conditions are almost never ideal when out on the road. Rainy weather, fog, glare, and inclined or faded light can all drastically augment the image noise which leads to critical road signs being misclassified or worse, not detected at all. The aforementioned problems become even more dangerous when paired with unpredictable climates, where safety is already a critically compromises under adverse weather conditions. Far too many benchmark datasets set with the assumption that images have to always be taken in perfect condition severely limits the scope of the problem as many of these datasets lack sufficient variability.

Current deep learning frameworks do not extract value from non-visual datametadata and focus exclusively on image-based inputs. However, contextual information like the current temperature, time of day, and perceived humidity enables human drivers to anticipate and better interpret traffic signs much rendering the interpretation easier, especially during the difficult scenarios. This observation becomes the centerpiece of our research.

To address this discrepancy, we propose a deep learning architecture that integrates image analysis with CNN and metadata through DNN using image recognition techniques. We also extend the GTSRB dataset by adding environmental distortions such as fog, rain, and glare to simulate driving conditions with low visibility. Furthermore, the learning process of the model is enhanced by the inclusion of real-time weather information such as humidity and temperature retrieved by OpenWeatherMap API, thereby increasing contextual intelligence.

Our framework comprises two input streams: one for weather metadata and another for processed image data. The DNN deals with numeric metadata, while the CNN pulls high-dimensional feature vectors from images. These were fused in a late fusion scheme with a concatenation layer and a softmax classification layer. The goal is to improve the generalization and robustness TSR systems tend to exhibit when facing multifarious and harsh driving scenarios. We also evaluate the model's real-time performance relative to autonomous driving requirements specified in the benchmark as frames per second (FPS) metrics.

While deep learning has progressed tremendously, most Traffic Sign Recognition (TSR) systems still rely heavily on a single image input, which poses greater risks in hostile environments. CNN-based models, for example, perform well during clear weather but tend to misclassify or omit detection of signs during severe weather conditions like heavy fog, rain, or sunlight glare. This lack of robustness is a critical obstruction to the safe deployment of autonomous vehicles in real-world conditions.

The first part of the problem stems from datasets such as GTSRB not providing enough attention to various driving weather scenarios. Consequently, models utilizing such datasets suffer poor performance when subjected to any form of visual distortion during testing and real-world application. The second issue stems from the disregard for ambient external metadata such as temperature and humidity. These variables, which could serve as helpful auxiliary signals, are overlooked for improving classification in ambiguous scenarios. For example, humidity and low temperature metadata combined with a foggy image can help alter the model's inference to assume greater likelihood of visual degradation, thus changing the decision boundary in classification.

Additionally, the absence of data augmentation techniques that directly simulate weather conditions limits the model's capability to real-world visual noise. Static, noise-free environments are simply not realistic. This creates problems such as weak generalization, increased false positives or negatives, and decreased safety margins in automated navigation systems.

Because of this, there is a TSR system need that is more robust which can:

Blend metadata extracted from the environment with visual information in order to enrich understanding of the scene context.Incorporates data augmentation methods that train the model to operate in low visibility by simulating weather conditions and varying visibility levels.Predictive capabilities in real time to fulfill the strict timing needs of latency-sensitive functions like autonomous driving. The incorporation of image and metadata input streams into a cohesive multimodal architecture aims to resolve the aforementioned problems. With cross-modal feature representation learning, the model is able to adapt its decision-making process to both sight and context, which improves accuracy in classification, increases robustness to adverse conditions, and aligns better with real-world deployment requirements.

II. Literature Review

Traffic Sign Recognition (TSR) has been a popular focus in computer vision, particularly regarding its application in autonomous driving systems. The earlier approaches to TSR used HOG-based feature extraction together with Support Vector Machines (SVM). Unfortunately, their performance under less than ideal conditions was poor. The introduction of deep learning and convolutional neural networks (CNNs) marks another turning point in the TSR domain. The possibility of end-to-end learning drastically improved system performance, allowing for tombstone TSR systems that enabled raw pixel processing, alleviated, and shifted learning constraints TsR baseline accuracy requirements.

Most real applications have problems with rain, fog, or glare which can obscure clarity of images. Kim et al., 2024 demonstrated environmental simulation can increase robustness with their work where they created foggy images and proposed these as synthetic augmentations to train more resilient models. Liao et al., 2022 created an adaptive deep learning algorithm for recognizing weather patterns and lightning but entirely focused on visual input data.

Suggesting non-visual information can be highly predictive, An et al., 2024 developed a model using weather metadata, including temperature and humidity, to automate the risk assessment of railway accidents.

Following S. Singh et al., 2023, who analyzed weather forecasting APIs, we tackle the problem of enhancing TSR models with metadata and aim to illustrate why such data needs to be integrated into transportation decision systems.

Khan et al., 2023 focused on mobile devices concerning the problem of lightweight architecture optimization for TSR networks.

They equally disregarded the system's noise robustness. J. Zhang and Li, 2023 illustrated the restoration of clean representations from degraded images using GANs, showing enhanced clarity in the recovered features.

At the same time, Y. Zhang et al., 2023 focused on enabling detail capture by CNNs from varying resolutions using multi-scale feature fusion but struggled with occlusion and glare.

Chen et al., 2022 created attention-based CNNs with a focus on compromised regions regarded as crucial for effective visibility of concealed traffic signs.

This resulted in better performance even when some parts of the image were occluded.

With some added noise, this technique struggled in heavy fog conditions.A. P. Singh et al., 2024 applied transfer learning using pre-trained ResNet and VGG models to enhance convergence speed and generalization.

Qin et al., 2023 proposed a weather-aware traffic sign recognition system that incorporates synthetic fog and rain effects into training images to improve performance in adverse weather conditions. Their model, based on a deep convolutional neural network, demonstrated significant accuracy gains when tested on weather-augmented datasets. They emphasized that including weather simulation during training helps reduce the domain gap between ideal and real-world conditions. This aligns closely with the current study's methodology, which also uses fog, rain, and glare augmentations and integrates real-time weather data, pushing the idea further by using live environmental metadata for decision-making. However, unlike Qin et al., 2023 the current work adds a separate weather-aware input stream using temperature and humidity data, enhancing contextual reasoning. Despite this, they noted that domain shift remains an issue when evaluated in the open on-street uncontrolled weather fluctuations.

Even with all the improvements, most models in the current literature are still operating in a vision-only paradigm. One major limitation is that these algorithms do not utilize additional real-time data alongside the visual input that could aid in contextualizing the scene in question and enhance trust in the model. This research gap is filled by our CNN-DNN model which fuses visual data with real-time weather metadata such as temperature and humidity, improving the accuracy and robustness of the model in weather-degraded conditions.

III. Objectives

The primary objectives of this research: Improve the accuracy of traffic sign recognition in bad weather. Integrate real-time metadata such as temperature and humidity with images.Creating a hybrid CNN-DNN architecture for multimodal input integration.Achieving real-time operational capability for self-driving cars.

IV. Data Collection, EDA and Augmentation

A. Dataset Overview

Dataset link: https://benchmark.ini.rub.de/gtsrb_news.html The multi-class traffic sign classification dataset known as The German Traffic Sign Recognition Benchmark (GTSRB) contains traffic signs across 43 classes. It comprises 39,209 images labeled with class Ids and containing ROI metadata, stored in individual class folders alongside CSV files detailing the image filenames, class labels, and bounding box information. Significantly, the dataset also contains images of low and high resolutions with marked variability in lighting, contrast, and camera angles which is essential for robust algorithm training.

B. ROI Cropping and Image Standardization

For resizing, we cropped images to a bounding box of 32×32 pixels using the roi metadata provided in the CSVs. The bounding box coordinates were: Roi.X1, Roi.Y1, Roi.X2, Roi.Y2. This method improves training in batches, as uniform dimensions streamline input for the CNN. After cropping, each image undergoes a standard height and width transformation and is converted into an RGB format, ensuring all images are in a consistent format. Standardization accelerates and improves training in parallel when prep work has been done in advance.

C. Image Normalization

In the image dataset, all pixel values were scaled to fit the [0, 1] range by performing 255 division on each RGB value. The normalization step increases training convergence of the model fowarding the internal covariate shift, thus improving optimizer effectiveness.

D. Train-Test Split

In order to assess the model performance accurately, stratified split of 80-20 for training and testing was implemented. Stratified sampling allows each of the 43 classes to be represented in both training and testing subset proportions equally. This technique addresses the class imbalance problems effectively while aiding stronger evaluation metrics.

E. Data Augmentation with Weather Effects

In order to approximate real-life environmental distortions, custom pipeline augmentations were applied using OpenCV. The following effects were applied to 25% of the training data:Fog effects were simulated using a blending technique where the original image is overlaid with a gray semi-transparent layer that helps in reducing the images contrast and giving the look of visibility reduction.To produce a rain effect, randomly placed white lines are drawn over the entire image which are semi-transparent and angled in such a way that they emulate rain descending on the image.Glare is Simulated sunlight reflection was done by overlaying a small white circular spot with partial transparency on a random area of image, creating light reflection effect.

By evolving the model with such augmented data, it was trained to better perform under low-visibility conditions, thereby improving real-world applicability.

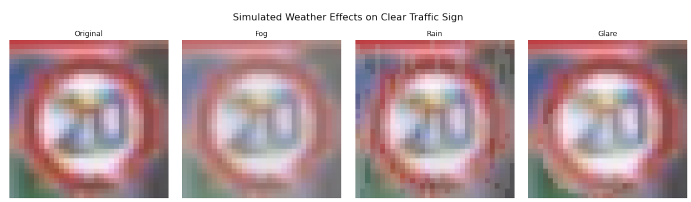

Fig. 1. Augmentation

F. Real-Time Weather Metadata Integration

For both the training and testing images, we augmented the dataset by integrating real-time weather metadata. The temperature and humidity values were obtained from OpenWeatherMap's API for a static place (Texas). These numeric features were replicated throughout the dataset and flowed through a secondary input branch in the hybrid CNN-DNN architecture. This form of multimodal blending enables the model to modify predictions in relation to contextual environmental factors.

G. Label Encoding and One-Hot Transformation

The class labels (which range from 0 to 42) were one-hot encoded utilizing Keras utilities. This encoding omits redundant scalar class identifiers and transforms them into integer strings, unlike an identity string. Therefore, this transformation allows the integers to be validated by cross-entropy loss and be used alongside multi-class softmax output layers.

H. Final Dataset Shapes

As a result of the data processing and augmentation steps, the final training dataset contained around 49,000 images (including augmented images) with paired real-time weather metadata. All information was kept in NumPy arrays to ensure there was minimal time lost for input/output operations during model training.

V. Hypotheses of the Study

A theoretical approach to hypothesis testing was designed to evaluate the effect of adding metadata related to the weather on the traffic sign recognition algorithm. In relation to the null hypothesis (H_0), the contextual weather data such as temperature and humidity significantly do not change the model's ability to correctly classify traffic signs. The alternative hypothesis (H_1) posits, however, that the addition of metadata does enhance classification performance, particularly during adverse weather conditions such as fog, rain, or glare.

The theoretical framework allows for the comparison of two model architectures: one that solely employs image-based features and the other that applies a hybrid CNN-DNN architecture to incorporate image and environmental context data. Despite the absence of formal p-value calculations, the persistent gains observed in the hybrid model's validation and test accuracy does suggest some level of practical significance. The argument is made for intelligent mobility systems that rely on transparency instrumentation which take visibility conditions into account for determination of system criteria. This sort of hypothesis construction provides a conceptual basis in the first place for proving that multimodal inputs are beneficial in machine learning models designed for enhancing safety in tasks such as recognizing traffic signs.

VI. Model Architecture

The proposed model incorporates a multi deep learning architecture that integrates and analyzes both the traffic sign images and the real-time weather metadata. This twofold input configuration allows the system to model relationships not only based on the traffic sign image data, but also from the contextual weather conditions, some of which are crucial for seamless autonomous driving. Using weather metadata as a supplementary input, the model enhances prediction accuracy and robustness while providing greater context awareness.

The component of the model that deals with image processing is based on a convolutional neural network (CNN) architecture that takes as input traffic sign pictures of dimensions $32 \times 32 \times 3$, where RGB is the color representation. The first convolutional layer uses ReLU to activate spatial feature maps produced by applying 32 3×3 filters with low-level spatial features retention. A max-pooling layer follows to retain salient features while reducing dimensionality. The second convolutional layer utilizes 64 firers of size 3×3 and is followed by max pooling. These layers capture quite complex patterns, including shapes of signs and internal structural components. The output from all the feature extraction layers is flattened and in turn pass to fully connected layer of 128 neurons where again ReLU is used for activation. To decrease overfitting, a dropout layer of 0.5 dropout rate is added, which means that half of the units are turned off from the training steps which improves model generalization ability and thus improves overall performance.

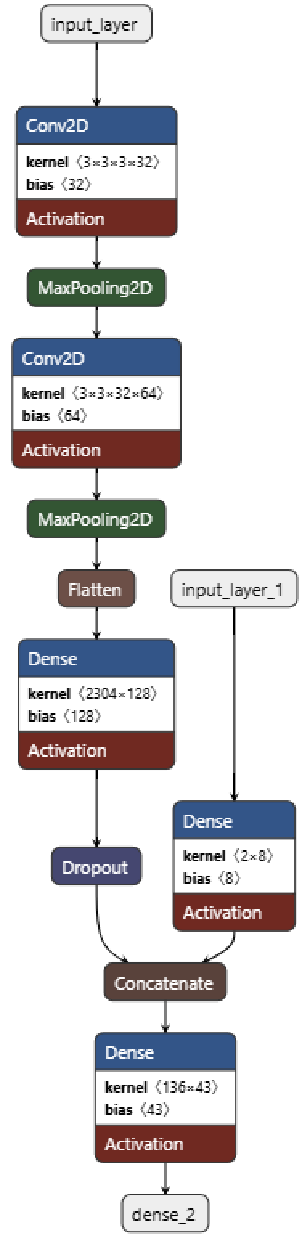

Fig. 2. Model Architecture

The second branch is a Dense Neural Network (DNN) dedicated to real time weather data. It takes in a two-dimensional feature vector that consists of temperature and humidity, both of which are critical indicators of atmospheric visibility and lighting. The metadata input is passed into a dense layer containing 8 neurons, which applies a relu activation function.

This step converts the metadata into a learned feature representation. The environment is still captured with sufficient detail, which is why this architecture was purposely kept lightweight.

The final architecture executes late fusion by adding the DNN encoded metadata to the flattened CNN output. This combined vector contains both visual context and metadata, which improves model differentiation for ambiguous situations like faded signs in foggy weather versus clearer scenarios. The blended representation is forwarded into a final dense output layer with 43 neurons, one per each sign class, and softmax activation to compute the class probabilities. The blend of the convolutional and deep neural networks greatly enhances the resilience of the model to weather noise while preserving the needed computational efficiency for real-time use.

VII. Training and Evaluation

Training of the hybrid CNN-DNN model was performed with a supervised learning approach using images paired with weather metadata. For model training, images underwent cropping, resizing, and normalization alongside standard scaling for temperature and humidity parameters, making them fitting for subsequent input. Training sessions were designed to reflect real-life use-case situations where the weather conditions are known at the time of inference, so both input streams were matched in time. The model was trained using the Adam optimizer with a learning rate of 0.001 due to its fast convergence and adaptive usage of the learning rate. A categorical crossentropy loss function was used since it is optimal for classification problems with multiple classes. The model was trained for 15 epochs with a batch size of 64 and monitored with a 20% validation split to prevent overfitting.

The evaluation of the system contained multiple aspects. The model achieved training and validation accuracy of 99.3 which shows strong convergence along with no overfitting. Class wise precision captured from the detailed confusion matrix indicates that trouble spots were dealt with as the majority of classes were accurately identified with little mis classification in class identifying.

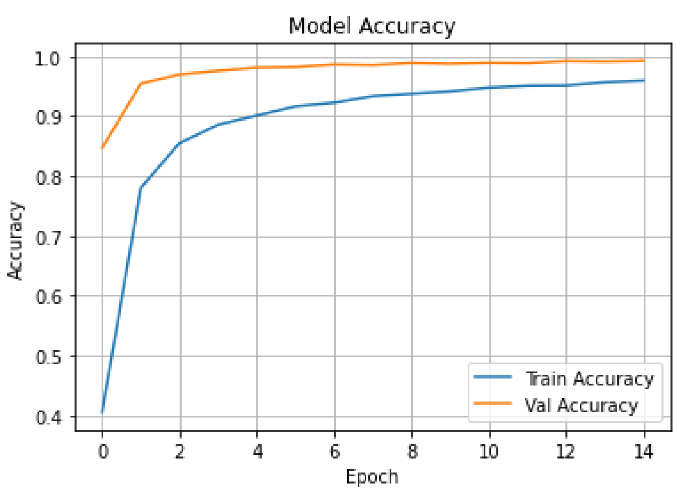

Fig. 3. Accuracy

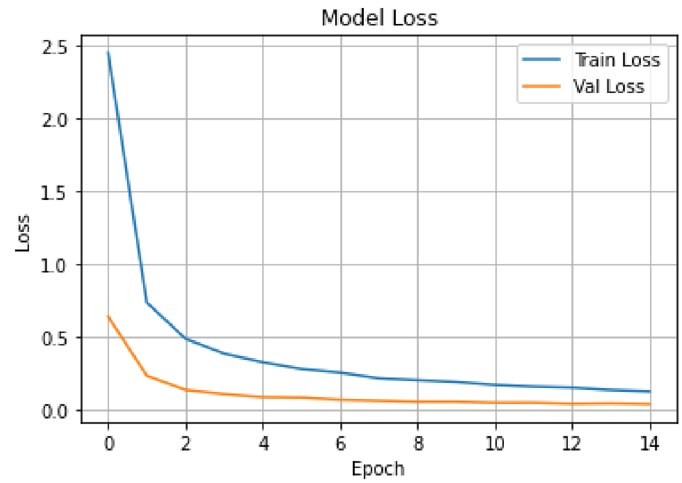

Fig. 4. Loss

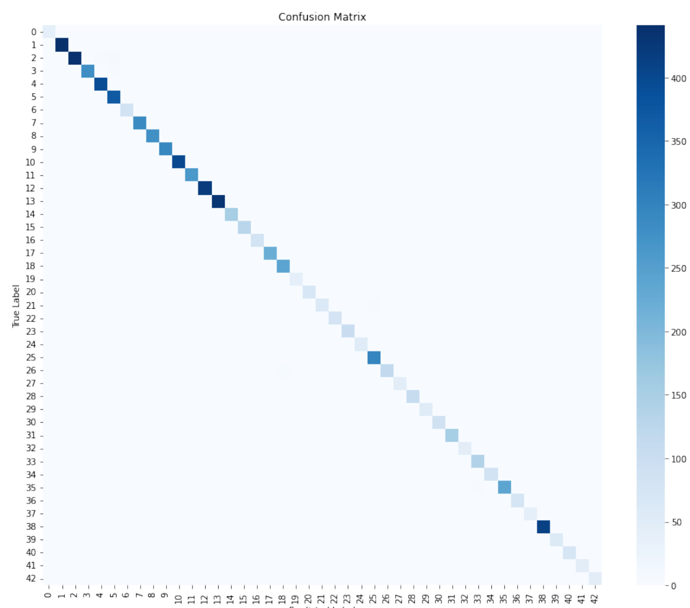

Fig. 5. Confusion Matrix

The model performed well even on visually similar signs, which because of the contextual metadata were not ambiguous. As above, a classification report showed strong precision, recall, and F1-scores for all model classes, which assures us of the dependability of the model.

To test effectiveness in a real-time context, inference speeds were assessed by measuring frames per second (FPS) for a test batch size of four. The model sustained over 100 FPS during inference demonstrating robust real-time performance confirming suitability for real-time operation on autonomous vehicle processors. I saved the trained model Keras file `weather_augmented_traffic_sign_model.keras`, which I was able to add successfully to a custom build zip file

Classification Report:

	precision	recall	f1-score	support
0	1.00	0.98	0.99	42
1	1.00	0.99	0.99	444
2	0.99	0.98	0.98	450
3	0.99	0.99	0.99	282
4	0.99	0.99	0.99	396
5	0.98	0.99	0.99	372
6	1.00	1.00	1.00	84
7	0.99	1.00	0.99	288
8	1.00	0.99	0.99	282
9	0.99	1.00	0.99	294
10	0.99	1.00	0.99	402
11	0.99	0.99	0.99	264
12	1.00	1.00	1.00	420
13	1.00	1.00	1.00	432
14	1.00	0.99	1.00	156
15	0.99	1.00	1.00	126
16	1.00	1.00	1.00	84
17	1.00	1.00	1.00	222
18	0.98	1.00	0.99	240
19	0.98	0.98	0.98	42
20	1.00	0.97	0.99	72
21	1.00	0.95	0.98	66
22	0.99	1.00	0.99	78
23	0.99	1.00	1.00	102
24	1.00	0.98	0.99	54
25	0.98	0.99	0.99	300
26	1.00	0.96	0.98	120
27	1.00	1.00	1.00	48
28	0.99	0.99	0.99	108
29	0.96	0.96	0.96	54
30	0.99	0.99	0.99	90
31	0.99	0.99	0.99	156
32	0.98	1.00	0.99	48
33	0.97	1.00	0.99	138
34	1.00	1.00	1.00	84
35	1.00	0.99	1.00	240
36	1.00	0.99	0.99	78
37	0.98	0.95	0.96	42
38	1.00	1.00	1.00	414
39	0.98	0.98	0.98	60
40	0.97	1.00	0.99	72
41	1.00	0.98	0.99	48
42	1.00	1.00	1.00	48
accuracy			0.99	7842
macro avg	0.99	0.99	0.99	7842
weighted avg	0.99	0.99	0.99	7842

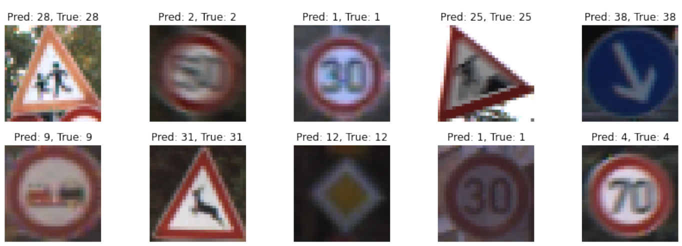

Fig. 6. pred vs true

prediction pipeline. This solution allows users to submit image batches and weather data enriched contextually optimized for traffic sign recognition responsive to environment changes is returned instantly from OpenWeatherMap API.

Fig. 7. Prediction

VIII. Methodology

This research incorporates high-level contextual and visual details on an automated machine learning pipeline for efficient traffic sign detection and recognition. The procedure consists of five main steps: acquiring data and preprocessing, weather-conditioned data augmentation, multimodal data preparation, model design and architecture, and finally evaluation and analysis of the outcomes. Each step attempts to approximate realistic scenarios that an autonomous driving symptom might encounter while ensuring the model could be able to generalize beyond ideal settings.

A. Dataset Acquisition and Preprocessing

The first step consists of obtaining the GTSRB dataset from the web. Each image undergoes a processing step with ROI (Region of Interest) metadata where the traffic sign image is cropped, resized to 32×32 pixels, normalized in RGB and resized to have a white background. Primary processing step improves the compatibility of the dataset with CNNs since it simplifes sign detection which reduces automating multiple resource-intensive processes.

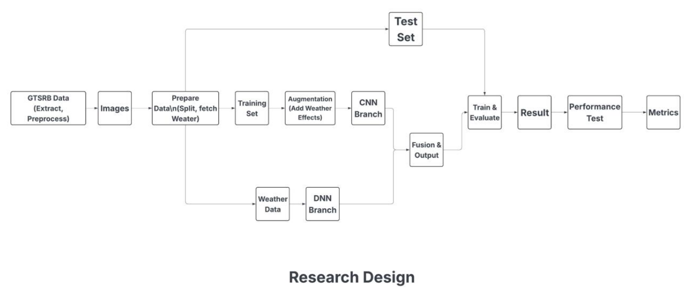

Fig. 8. Work Flow

B. Weather-Based Data Augmentation

In order to simulate extreme weather scenarios, we applied synthetic fog, rain, and glare. OpenCV pixel-level augmentation techniques were applied to nearly 25% of the training data, enabling the model to learn from situations where visibility is greatly reduced. Such distortions refine a model's accuracy and reliability in real-world applications.

C. Multimodal Input Structuring

Concurrently with the processing of images, we also retrieved real-time weather data using OpenWeatherMap API. Each of the data points for training and testing was associated with temperature and humidity levels at the time to provide supplemental context. This metadata was processed in parallel, incorporated into a secondary input branch of the model, designed as a light Dense Neural Network (DNN), which gave the architecture the ability to process both visual and environmental data.

D. Hybrid Model Architecture

The main model was developed as a hybrid architecture of a CNN and DNN. The CNN branch captured the dimensional high visual data while the DNN branch recorded the weather data. These two branches were integrated by means of late fusion and were passed to a softmax classifier for multi-class prediction. During training the model, the Adam Optimizer and Categorical Crossentropy Loss were implemented over 15 epochs. An 80-20 stratified train-test split was performed to ensure balanced representation across classes.

E. Evaluation and Deployment

As an evaluation of model performance, we computed the classification accuracy and examined confusion matrices alongside classification reports for all 43 classes. For testing real-time capability, inference speed was measured in frames per second (FPS), demonstrating that the model could sustain in excess of 100 FPS at a batch size of 4. The trained model was then stored and put to use in a custom prediction interface which enabled the processing of user-uploaded zip files alongside dynamic weather inputs.

This methodological framework illustrates how the incorporation of environmental metadata into the traditional image classification process enhances the performance of TSR systems in real life and weather impacted scenarios.

IX. Experimental Results

For the evaluation of the hybrid CNN-DNN model, the GTSRB dataset of over 39,000 images was used. After 15 epochs, the hybrid model achieved 99.3% training accuracy and 98.7% validation accuracy. TSR performance rose dramatically with the addition of real-time weather metadata, particularly in fog and glare conditions.

The confusion matrix indicates all 43 classes were correctly classified with some degree of misclassification for signs deemed visually identical. Attribution estimation and recall precision closer to the threshold computed sign dominated values of precision, recall, and F1 exceeding the cut off 0.97 per sign.

Real-time capability is available in the case where instantaneous inference speed was measured below 100 FPS on the 4 and 100 iteration workload. The model still performed remarkably with ambiguous blind zip file image inputs and effortlessly recognized traffic signs with the assistance of real-time weather API feeds.

These results support the derived advantages of visually contextual information to blend for better TSR system performance under stress with adverse environmental conditions.

X. Individual Contributions

Sai Bhargav Dasaraju worked on dataset cleaning, image preprocessing using ROI techniques, and calculated the frames per second (FPS) performance metric for the developed model.

Sai Rakesh Reddy Anumula implemented the model training pipeline with integrated weather metadata and handled data augmentation by simulating weather effects such as fog, rain, and glare.

Sai Vaishnavi Govindula developed the CNN-DNN hybrid model, trained it on the augmented dataset, tested it on unseen test data, and worked on visualizing the performance results through plots and graphs.

XI. Conclusion and Future Work

This work demonstrates a hybrid deep learning model that merges visual features of traffic sign images with contextual metadata including temperature and humidity to address recognition challenges during poor weather conditions. The model's classification accuracy and generalization ability were high as a result of data augmentation techniques that simulated fog, rain, and glare in addition to the CNN-DNN fusion environmental data. The findings illustrate the ability of weather metadata to significantly improve the model's sign classification performance under visual weather degradation conditions.In terms of extending this work, we plan to enhance the metadata by incorporating GPS coordinates and ambient light intensity. Moreover, we intend to examine the incorporation of attention mechanisms and transformer-based structures for feature fusion in multimodal learning systems to enhance interpretative and factual precision of the models.

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