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# 1

## Timing Analysis of Synchronous Neural Networks





# 2

## Run-time Enforcement of Synchronous Neural Networks



# 3

## Run-time Verification of Synchronous Neural Networks

### 3.1 Methodology

The system designed for this case study was made to reflect a Autonomous Vehicle (AV) and its object detection mechanisms. The system used multiple techniques to tackle the inherent issues of the AV system, i.e. weakness to perturbed inputs and misclassification detection. The system’s sensors include an overhead, 360° Light Detection and Ranging (LiDAR) apparatus, and a single, frontal facing camera. A solitary camera was sufficient to prove the efficacy of this solution, however it is to be noted that AV systems generally use multiple cameras, facing different directions, so that the controller can make properly informed decisions. The system used can be seen in Figure 3.1.

The LiDAR for this system was accurate 93% of the time [5], to closely simulate a real LiDAR system. The simulated camera outputs consisted of test images from both the Visual Object Classes (VOC) [1] and German Traffic Sign Recognition Benchmark (GTSRB) [4] datasets, in a combination of people, vehicles and various traffic signs. The LiDAR and camera outputs were handled by different parts of the controller. The camera outputs were fed into a Meta Neural Network (MNN) (see Figure 3.2) where they were classified by shape, colour and object.

Utilising synchronous semantics, a Meta Neural Network (MNN), containing three other MNN ensembles, was created. Each ensemble synchronously combined the outputs of three different Synchronous Neural Networks (SNNs) [3], providing increased prediction accuracy for each aspect.

The system controller was encapsulated by a run-time enforcer [2] that used sensor fusion to check for misclassifications made by the MNN. If a misclassification was detected, the enforced policy entered an unstable state. Once enough time passed without further misclassifications, the vehicle entered a safe state again. However, if another misclassification was detected, the enforced policy entered a violation state, forced control of the AV away from the controller and gave control to the driver. The vehicle would not enter autonomous mode again until the system was restarted. A diagram of the enforced policy’s safety automaton is shown in Figure 3.3.

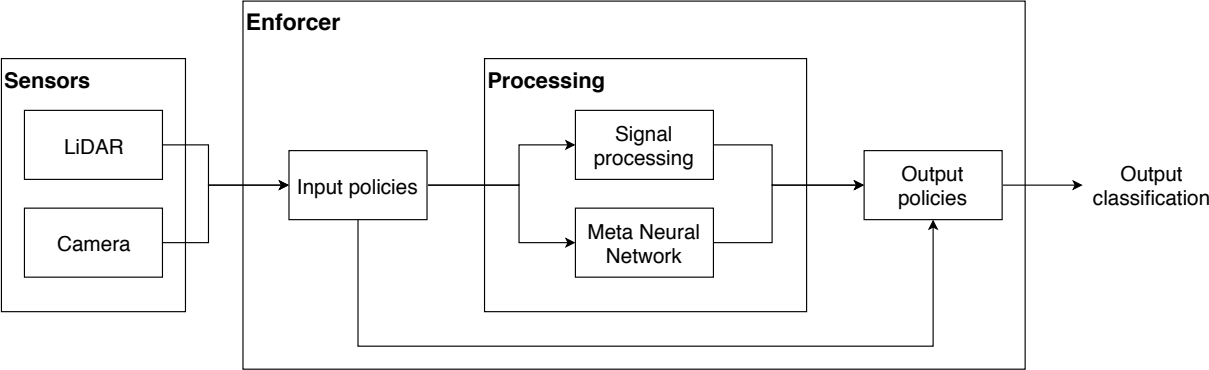


Figure 3.1: Block diagram showing the AV system with enforcer

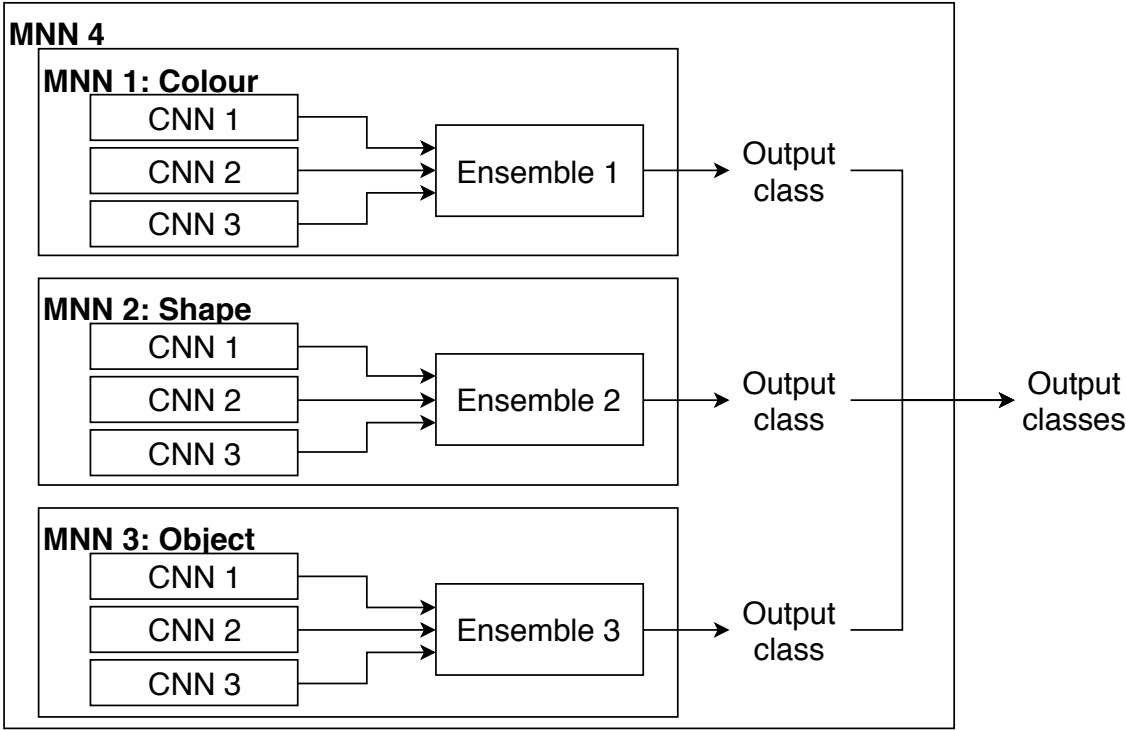


Figure 3.2: Block diagram showing the Meta Neural Network ensemble.

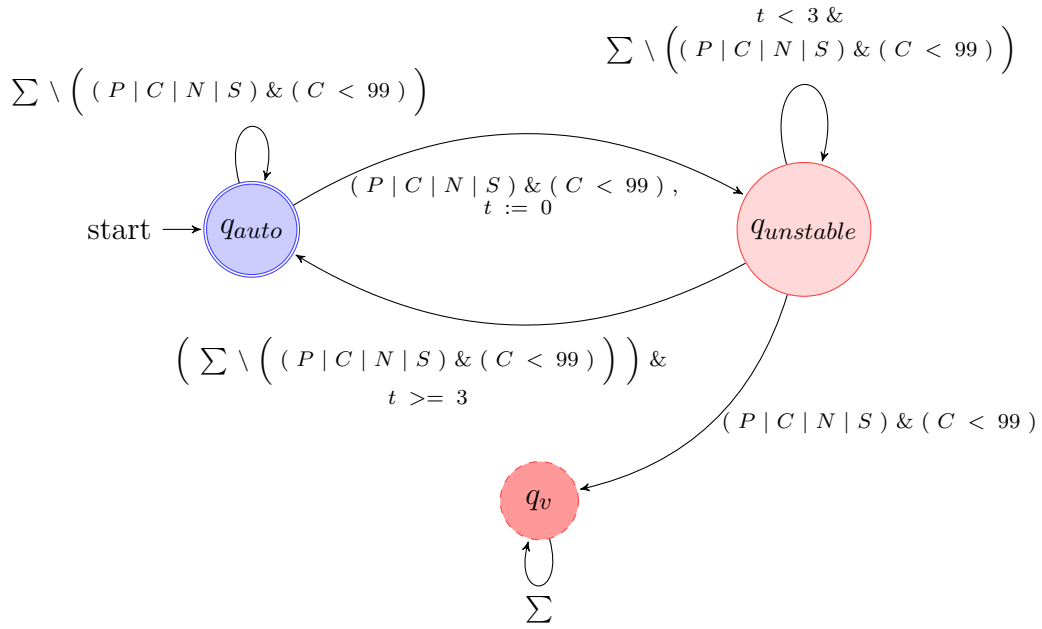


Figure 3.3: Enforcer policy for the AV prediction system

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Test case	Person	Vehicle	Nothing of relevance	Street sign	Total
Number of misclassifications	3.45	9.29	6.65	38.56	57.96
Caught misclassifications	3.06	8.83	6.51	37.45	55.85
False negatives	3.87	2.16	0.28	7.53	13.84
Missed misclassifications	4.26	2.62	0.42	8.64	15.94

Table 3.1: Table showing results of the AV prediction SNN using perturbed images

## 3.2 Results







# Appendix



# References

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