**Experiments 2:** we provide instructions to generate the safety case, and we provide domain knowledge, and we do not specify GSN syntax (i.e., no GSN structural rule is specified, and no example of GSN syntax is provided).

**Prompt:**

You are a professional safety case developer assistant. I want you to create a safety case for the given system in Goal Structuring Notation (GSN) Format.

I will give you the following information in the form of Questions and Answers:

Question 1: What is a safety case?

Answer: A safety case is a structured argument, supported by evidence, intended to justify that a system is acceptably safe.

Question 2: What is the format of the safety case

Answer: I want you to generate a safety case in GSN Format

Question 3: What is the system for which you need to generate a safety case

Answer: The system is a Machine Learning (ML) algorithm that is used to implement the classification function of a Tire Noise Recognition (TNR) component of a vehicle. Tyre Noise Recognition (TNR) component is used to improve multiple vehicle-level functions. The TNR makes use of microphones positioned within the wheel housing to measure road surface noise to determine, in real time, whether the road is dry. Here, dryness is defined as a road surface without any materials between tyre and road surface. This classification is, in turn, used as an additional source of information by chassis control and powertrain systems to determine the current surface traction and thereupon adapt control parameters accordingly, i.e., a !dry surface requires adaptations for a consistent traction.

Question 4: What is the main objective of the safety case

Answer: The objective of the safety case is to develop a structured and convincing argument that the classifier fulfilled its technical requirements, with respect to functional insufficiencies that could lead to False Positives (FP) identifications of dry road surface conditions.

Question 5: Additional Context about the system

In order to provide accurate information to the chassis control system, the TNR must process the audio signal with strict real-time requirements and be able to filter sampling anomalies caused by conditions such as the impact of loose gravel. Due to the runtime properties as well as the ability to process a wide range of signal patterns based on available data, a ML technique was chosen to implement the classification function of the TNR. Through limits imposed within the vehicle-level function, the remaining safety concerns regarding the ML-based classification were low enough to assign only Quality Management (QM) requirements to the TNR after completing the hazard and risk analysis according to ISO 26262. However, in order to increase the functional benefits of the vehicle-level function through usage of TNR information, it was decided to evaluate the impact of reducing the limits imposed within the vehiclelevel function. This in turn placed an increased safety load onto the TNR and hence led to the following functional safety requirement (FSR) allocated to the TNR:

– FSR x: The TNR shall not provide the result dry in case of a non-dry road surface (ASIL B).

In order to focus on factors affecting safety, the following relationship between classified and actual prevailing road surface condition was established:

– True-Positive (TP) Predicted dry while actually dry

– True-Negative (TN) Predicted !dry while actually !dry

– False-Negative (FN) Predicted !dry while actually dry

– False-Positive (FP) Predicted dry while actually !dry

Predicted dry while actually dry, Predicted !dry while actually !dry, Predicted !dry while actually dry, Predicted dry while actually !dry.

The misclassification FN only results in an overly conservative control strategy as higher traction is not actually needed but still activated, thereby not violating any safety goals. Hence, only the misclassification FP, which corresponds to FSR x, is safety-relevant.

Question 6: Are there any evidences?

The following methods were identified to provide explicit evidence corresponding to the V&V objectives. In some cases, existing evidence could be aligned with the V&V objectives, in other cases, additional tests and associated documentation were required. – Analysis: An understanding of the strengths and weaknesses of the chosen ML technique and model provided evidence for the inherent properties regarding robustness and generalisation. In addition, the prototypes generated by the algorithm (cf. Section 5) were amenable to examination by subject matter experts to confirm that they corresponded to known properties of the dry and! dry signals.

– Simulation: A simulation environment based on synthetic and recorded data was used for a focused verification of ML properties. Here, signal noise can also be simulated to verify the robustness of the classifier.

– Structured testing: The domain model was used to determine a set of test cases which cover all known properties which could influence the performance of the function. In addition, the test cases also included specific corner cases discovered during field tests and added to the regression test set.

– Field tests: Field tests, where the function was tested on real roads (both test track and public roads) were performed according to selected properties of the domain model. This allowed the coverage of conditions to be evaluated. Anomalies which could not be explained by the parameters of the domain model were used to iteratively refine the domain model.

Create a top-level safety case for the ML algorithm in GSN Format