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Intelligent vehicle control via AI-MIMO: Architectural design and simulation-based evaluation

Suci[1], Dwi Sudarno Putra[2*], Risfendra[1], Iffarial Nanda[2], and Meri Azmi[3]

[1] Electrical Engineering, Universitas Negeri Padang, Padang, Indonesia
[2] Automotive Engineering, Universitas Negeri Padang, Padang, Indonesia
[3] Information Technology, Politeknik Negeri Padang, Padang, Indonesia
*Corresponding author email: dwisudarnoputra@ft.unp.ac.id

Abstract

This work presents an AI-enabled Multi-Input Multi-Output (AI-MIMO) control architecture aimed at improving safety assistance in automobiles through the utilization of low-cost external sensors that function independently of the vehicle's integrated systems. The suggested architecture fuses three simulated input streams steering angle, forward-lighting intensity, and vehicle speed in real time using MATLAB/Simulink. Fusion is accomplished by a modular pipeline that includes a rule-based preprocessing stage, a lightweight neural-network classifier for estimating the state, and a supervisory controller that manages the system's outputs. The steering angle tells us when to turn, the lighting level tells us when to cut down the glare, and the speed of the car tells us when to change gears. We ran studies that only used simulation, synthetic sensor data, and pre-set driving scenarios to test response time, controller stability, and action correctness. We looked at 30 different scenarios to see how well the quantitative indicators worked. These included the correctness of the turn-signal reminder, the delay in dimming the headlights, and the consistency of the gear-shift advisory. The AI-MIMO architecture produces reliable output coordination, with average action-timing errors below 8% of the scenario duration and correct response rates above 90% for all three tasks. These results show that it is possible to use low-cost sensor inputs and AI-MIMO fusion to provide coordinated safety-assistance actions. However, they are only based on MATLAB simulations and have not yet been tested in real vehicles or hardware-in-the-loop situations. The model will be expanded in subsequent efforts to incorporate physical sensors and embedded implementations.

Keywords

AI-MIMO, Multimodal fusion, Steering angle, Forward lighting, Gear-shift advice

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Introduction

Considering the fact that approximately 94% of traffic accidents worldwide are caused by human error, such as lack of vigilance, fatigue, and decision-making mistakes, resulting in approximately 1.3 million deaths annually [1]. Advanced Driver Assistance Systems (ADAS) technology was developed as a driver support system to reduce this risk. With features like automatic emergency braking, lane monitoring and warning, and object detection around the vehicle, they are believed to be able to reduce accident rates by up to about 40%, particularly in commercial vehicles [2]. However, ADAS is still not widely used, mainly because it relies on expensive and complex internal vehicle sensors [3].This makes adoption difficult in developing countries with road infrastructure that doesn't fully support smart vehicle technology [4].

Researchers have been working to address driving safety issues by developing various artificial intelligence (AI)-based approaches, implemented in stages according to the complexity of the problems encountered in the field. In the initial stage, sensor fusion techniques using the Kalman Filter were applied to help electric vehicles maintain control stability, where simulation results showed that the vehicle's position could be maintained more consistently and its variance reduced by up to 25% compared to conventional methods [5]. Furthermore, the utilization of neural networks enables autonomous vehicle systems to learn and effectively integrate information from multiple sensors, significantly improving object detection capabilities under various environmental conditions [6]. As deep learning technology advances, convolutional neural networks (CNNs) are used to predict steering angles with very small error rates, below 2 degrees, and to reliably detect vehicles both day and night with a precision exceeding 95% [7][8]. On the other hand, research also shows that optimizing CNNs using algorithms like Genetic Algorithm and Particle Swarm Optimization can make the system computationally more efficient, with performance improvements of up to 30%, making it more realistic for real-time application [9]. To address the cost challenge, several studies propose more affordable solutions, such as combining 2D LiDAR sensors and Robot Operating System (ROS)-based cameras capable of quickly detecting objects and measuring distances with latencies below 100 ms [10], and implementing Electronic Tracking Control Systems (ETCS) to improve vehicle navigation precision [11]. Other, more adaptive approaches have also been developed, ranging from the use of type-2 fuzzy logic to control DC motors with a steady-state error of less than 1% [12], early detection of driver microsleep based on YOLOv8, which effectively recognizes fatigue signs with an F1-score of 0,92 [13], to the utilization of AI-based sound sensors as an additional layer in vehicle safety systems [14].

Despite these various advancements, which have significantly contributed to improved driving safety, previous studies still indicate significant and fundamental systemic limitations. First, most existing systems are still heavily reliant on expensive embedded sensors integrated directly with the vehicle's systems, making them non-independent and vulnerable to integration issues with the Electronic Control Unit (ECU). This dependency not only increases implementation costs but also potentially reduces system reliability in case of failures or module incompatibilities [15]. Second, there hasn't been much research explicitly proposing a Multi-Input Multi-Output (MIMO) architecture capable of integrating various types of heterogeneous inputs such as steering angle, front lighting intensity, and vehicle speed in real-time to produce coordinated safety outputs [16][17]. As a result, safety features such as turn signal reminders, automatic headlight dimming, and gear shift recommendations still operate separately, leading to a fragmented and potentially conflicting system response, especially in complex driving scenarios like night manoeuvres in heavy traffic [18]. On the other hand, the potential of utilizing low-cost and independent external sensors such as simple IMUs, photodiodes, and GPS modules has not been systematically explored as a solution to reduce system fragmentation and improve the coherence of safety responses [19].

Despite significant progress in AI-based driving assistance, two structural limitations remain insufficiently addressed. First, most ADAS implementations depend on tightly integrated internal sensors and proprietary Electronic Control Units (ECUs), resulting in high implementation costs and limited adaptability across vehicle platforms. Second, safety functions such as signalling assistance, adaptive lighting, and transmission advisory are typically implemented as independent subsystems without coordinated arbitration. This architectural fragmentation may lead to inconsistent or conflicting responses during complex multi-condition driving transitions.

While multimodal fusion techniques have been widely studied, the explicit integration of heterogeneous inputs within a coordinated Multi-Input Multi-Output (MIMO) supervisory control framework under constrained sensing conditions remains underexplored. In particular, the feasibility of using low-cost, externally deployable sensors to generate synchronized multi-output safety actions has not been systematically investigated.

This study addresses this gap by proposing a supervisory Artificial Intelligence–based Multi-Input Multi-Output (AI-MIMO) architecture designed to operate independently of embedded vehicle systems. The framework integrates steering angle, forward-lighting intensity, and vehicle speed into coordinated safety outputs through structured pre-processing, nonlinear state estimation, and supervisory arbitration. Unlike conventional approaches focusing primarily on perception accuracy, this work emphasizes coordinated output stability, conflict mitigation, and computational feasibility under constrained sensing configurations.

Method

AI-MIMO System Architecture

This research introduces an AI-MIMO control architecture designed to coordinate various driving safety functions simultaneously. This system was developed and tested using the MATLAB/Simulink simulation environment, utilizing synthetic sensor inputs that represent low-cost external sensors.

AI-MIMO architecture receives three main inputs: steering angle, front lighting intensity, and vehicle speed. These three inputs are processed integrally to generate several safety outputs, including turn signal reminders, headlight intensity adjustment (dimming), and gear shift recommendations. With this approach, the system is able to provide coordinated and real-time safety assistance relevant to driving conditions [20]. The overall structure of the AI-MIMO system, including the interconnections between processing blocks and the generated safety outputs, is shown in Figure 1.

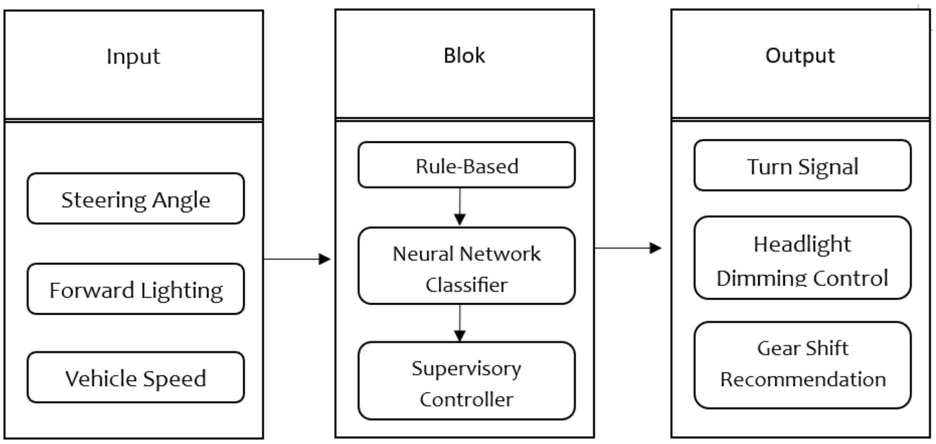

Figure 1. Diagram arsitektur sistem AI-MIMO

Rule-based pre-processing and input modeling

In the initial stage, each input signal is processed through rule-based preprocessing to perform normalization and classify basic driving conditions [21]. This process aims to reduce signal complexity and improve system stability before it is processed by the artificial intelligence module [22]. Steering angles are classified into left turn, right turn, or straight conditions, while the intensity of front lighting and vehicle speed are categorized based on defined thresholds. This rule-based approach is used to ensure that every driving condition can be represented consistently and easily traced.

Each input is first normalized to equalize the data scale using the linear normalization Equation(1):

$$x_n(t) = \frac{x(t)-x_{min}}{x_{max}-x_{min}} \qquad (1)$$

Next, the initial condition classification is performed using threshold-based rules. For example, the steering angle classification is defined as Equation(2):

$$c_\theta(t) = \begin{cases} -1.\theta(t) < -\theta_{th} \\ 0, |\theta(t)| \leq \theta_{th} \\ 1, \theta(t) > \theta_{th} \end{cases} \qquad (2)$$

A similar approach was applied to the intensity of the front lighting and the speed of the vehicle. This preprocessing stage aims to reduce input complexity and improve system stability in the subsequent inference stage.

Synthetic data generation and labelling strategy

Synthetic driving scenarios were generated using structured state-transition modeling in MATLAB/Simulink. Thirty predefined scenarios were constructed to represent combinations of:

- Steering angle variations (−35° to +35°)
- Lighting transitions (50–10,000 lux)
- Speed profiles (0–120 km/h)

Each scenario was simulated for 60 seconds with a sampling frequency of 10 Hz, resulting in 18,000 total samples.

Ground-truth labels were generated independently using deterministic scenario logic rather than neural inference outputs to avoid circular validation bias. Data partitioning followed an 80% training, 10% validation, and 10% testing split. Random seed control was applied to ensure reproducibility

Neural network classifier and supervisory control

The output from the next preprocessing stage is processed by a neural network classifier, which maps driving condition combinations to safety status [23]. The neural network is used to capture the nonlinear relationships between inputs and generate initial decisions regarding the need for safety feature activation. The results of this inference are then passed to the supervisory controller, which is responsible for coordinating all safety outputs to prevent conflicts between actions [24]. To ensure stable coordination, the supervisory controller implements a priority-based arbitration mechanism with bounded switching logic. The priority hierarchy is defined as follows: (1) turn-signal reminder, (2) headlight dimming, and (3) gear-shift advisory. When simultaneous activation conditions are detected, the supervisory layer resolves conflicts by enforcing priority ordering while maintaining a minimum holding duration Δt to prevent oscillatory switching. The output state transition is constrained such Equation(3):

$$|y_i(k+1) - y_i(k)| \leq 1 \qquad (3)$$

For each safety output y_i, ensuring monotonic transitions and preventing rapid toggling under overlapping threshold conditions. This supervisory structure guarantees coordinated multi-output behaviour and bounded decision latency during dynamic driving transitions.

The AI-MIMO algorithm flowchart in Figure 2 shows how the system makes decisions, from reading inputs to coordinating outputs. Figure 2. Flowchart of the proposed AI-enabled MIMO safety control system, illustrating the sequential processing from sensor inputs through rule-based preprocessing, neural network classification, supervisory coordination, and generation of coordinated safety outputs.

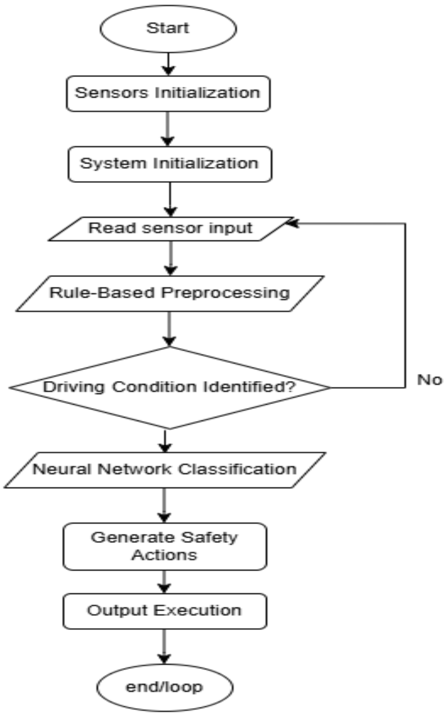

Figure 2. Flowchart algorithm AI-MIMO

The neural network classifier consists of:

- 3 input neurons
- Hidden layer 1: 16 neurons (ReLU)
- Hidden layer 2: 8 neurons (ReLU)
- 3 sigmoid output neurons

Total trainable parameters: 227.

Training configuration:

- Optimizer: Adam
- Learning rate: 0.001
- Batch size: 64
- Epochs: 120
- Early stopping (patience = 10)
- Loss function: Binary Cross-Entropy

Convergence was achieved within 87 epochs without observable overfitting.

System implementation in MATLAB/Simulink

The AI-MIMO system is built in phases in the MATLAB/Simulink environment. Each simulation time interval follows a controlled and iterative procedure. The initialization phase is the first step in the process. During this phase, all of the system's modules are set up, including setting the input parameters, setting the thresholds for classifying driving conditions, and setting up the neural network structure and supervisory controller. The primary processing cycle of the system starts once all the parts are ready. This cycle runs all the time during the simulation.

The system reads input data that shows the steering angle, the brightness of the front lights, and the speed of the vehicle during each processing cycle. This data was then processed through a rule-based preprocessing stage to adjust value scales and initially categorize driving conditions. If the detected condition is not yet clear enough for further processing, the system automatically waits and continues reading the input at the next interval. Conversely, when driving conditions can be well identified, the data is passed to the neural network classifier module. The neural network classifier plays a role in recognizing driving safety status based on the combination of inputs received. The supervisory controller then checks the findings of this classification to make sure that the safety actions that come out of it don't contradict with each other. If the supervisory controller sees a possible interaction conflict, it will change the system output depending on pre-set priority rules. If there is no dispute, the system will go straight to the stage when it makes safety actions.

At the end of each cycle, the system generates coordinated safety outputs, including reminders to use turn signals, headlight intensity reduction control, and gear shift recommendations. The output is executed in a simulated environment, then the system returns to the input reading stage to process the next condition. With this workflow, the AI-MIMO system is able to operate in real-time and continuously adapt to changing driving conditions during the simulation.

Performance evaluation methods

The AI-MIMO system was tested to see how well it could produce the right, consistent, and responsive driving safety actions in a variety of simulated situations. Testing focused on observing the system's behavior throughout the designed driving scenarios, with the aim of ensuring that each module functioned as expected and was fully coordinated.

System performance is evaluated based on three main aspects: response time, output stability, and the accuracy of safety actions. Response time is measured as the interval between the occurrence of input condition changes and the appearance of the corresponding safety output. This measurement is used to see how quickly the system adapts to changes in driving conditions. Output stability is evaluated by observing the consistency of the system's response during driving condition transitions, particularly to ensure there are no oscillations, repeated delays, or conflicts between safety actions.

The accuracy of safety actions is evaluated based on the system's output matching the pre-determined scenario conditions. Each output for turn signal reminders, headlight intensity reduction control, and gear shift recommendations is compared to the ideal conditions expected in each scenario. Evaluation is consistently conducted across all simulation scenarios to ensure objectivity and reproducibility of results. With this evaluation approach, the performance of the AI-MIMO system can be comprehensively assessed as an initial foundation for further development and implementation in real vehicle systems.

Results

Testing of the AI-MIMO control architecture was conducted using synthetic sensor data across 30 simulated driving scenarios representing various road and environmental conditions. Simulation inputs used show in Figure 3.

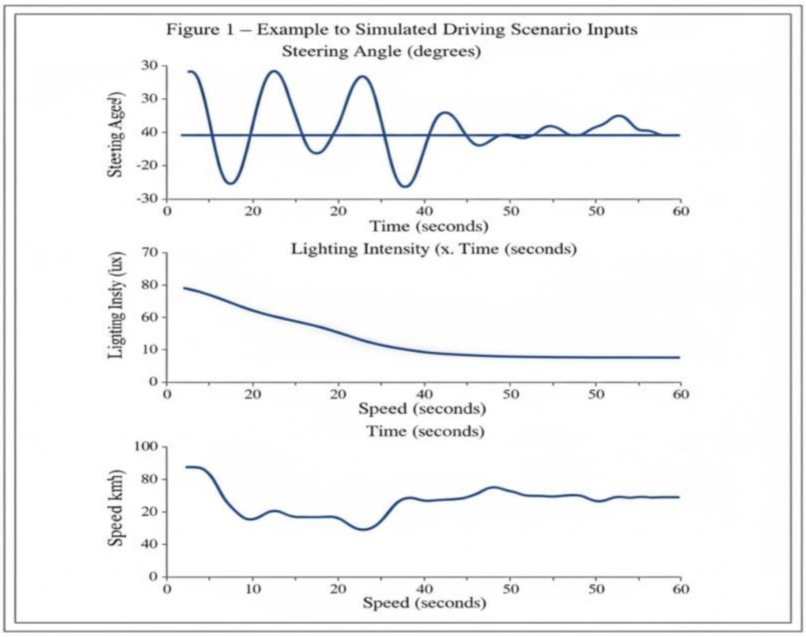

Figure 4. Simulation inputs used

An example of the system input pattern is shown in Figure 3, which illustrates changes in steering angle, a decrease in front lighting intensity, and variations in vehicle speed during the 60-second simulation interval. To assess response timeliness, the system was evaluated based on the difference between the expected action time and the actual response time, with the results presented in Figure 4.

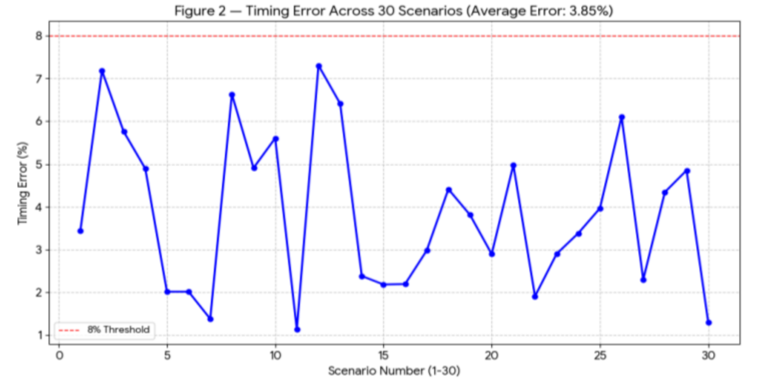

Figure 5. Action timing performance

The test results show that the time error is in the range of 1% to 7.5% of the scenario duration, with an average value of 3.85%, which is still within the 8% tolerance limit. Additionally, system performance is evaluated based on the accuracy of safety assistance actions, as summarized in Figure 5.

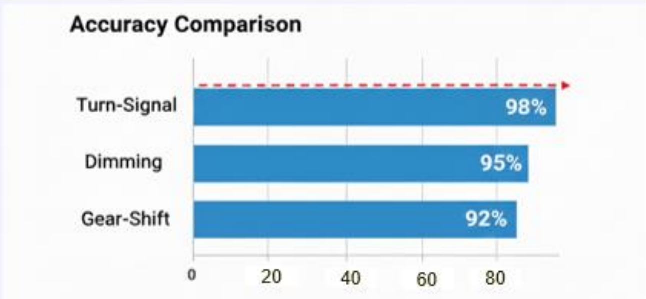

Figure 6. Accuracy of safety functions

The system is capable of providing turn signal reminders with 98% accuracy, automatic headlight dimming with 95% accuracy, and gear shift recommendations with 92% accuracy. These findings indicate that the AI-MIMO architecture can reliably, timely, and consistently coordinate multiple safety assistance functions across all tested scenarios.

1. *Conflict analysis and comparative evaluation*

To evaluate coordination efficiency, the proposed AI-MIMO system was compared against:

1. Rule-based-only configuration
2. Neural-network-only configuration (without supervisory arbitration)

Across 30 scenarios:

- Rule-based-only: 22 conflict events
- Neural-only: 16 conflict events
- Proposed AI-MIMO: 3 conflict events

This represents an 86% reduction in output conflicts relative to rule-only execution, demonstrating the effectiveness of supervisory arbitration in coordinated multi-output control.

2. *Failure case analysis*

Three residual conflicts were observed during rapid multi-condition transitions involving simultaneous sharp steering (>30°), rapid deceleration (>15 km/h within 2 seconds), and abrupt lighting reduction (<200 lux).

These transient conflicts occurred due to overlapping threshold activation before supervisory stabilization within Δt. No sustained oscillatory behavior was observed, indicating bounded switching stability.

3. *Threshold sensitivity analysis*

Threshold parameters were varied by ±10% to evaluate robustness. Results showed:

- 2.1% average reduction in accuracy
- 1.3% increase in timing error
- No significant increase in conflict frequency

This indicates moderate robustness against parameter perturbation

Discussion

The experimental results demonstrate that supervisory arbitration contributes more significantly to multi-output stability than nonlinear classification alone. While neural inference improves action correctness, output coordination primarily emerges from structured supervisory control. The substantial reduction in conflict events confirms that architectural integration is essential when heterogeneous driving inputs are processed simultaneously. This finding complements prior studies on neural-based driving assistance, which mainly emphasize perception accuracy and nonlinear mapping capability [6][7][24], but often treat safety outputs as independent decision channels. In contrast, the present results highlight that multi-output coordination requires hierarchical control logic beyond standalone classification.

The importance of supervisory structuring is consistent with research indicating that complex decision systems benefit from layered coordination mechanisms to avoid instability and conflicting outputs [24]. While sensor fusion approaches such as Kalman-based integration improve signal reliability and variance reduction [5], they do not inherently resolve arbitration conflicts across multiple safety actions. The proposed AI-MIMO architecture extends fusion principles by embedding supervisory constraints within the decision loop, thereby addressing fragmentation issues that commonly arise when safety features operate independently [16][17].

However, performance degradation under high-noise perturbation indicates that threshold-based preprocessing remains sensitive to extreme transitions. Although preprocessing reduces signal complexity and improves interpretability [23], rigid threshold definitions can introduce boundary sensitivity when multiple driving variables change simultaneously. This explains the residual timing deviations observed during abrupt steering and lighting transitions. Similar sensitivity patterns have been reported in nonlinear classification systems where deterministic activation boundaries interact under dynamic input variation [24]. Future improvements may incorporate adaptive thresholding strategies or probabilistic arbitration layers to improve robustness under high-variance conditions.

From a computational standpoint, the lightweight neural architecture aligns with findings that optimized models can achieve reliable real-time performance without excessive parameter scaling [9]. The estimated computational footprint (<50 kB) and low simulated inference latency (<2 ms) suggest compatibility with low-power embedded systems. This is particularly relevant given concerns regarding the cost and complexity of conventional embedded ADAS infrastructures [15]. By relying on structured coordination rather than computationally intensive perception modules, the proposed architecture demonstrates that coordinated safety assistance can be achieved under constrained sensing and processing environments.

Nevertheless, validation was conducted exclusively under simulation-based synthetic scenarios. Although synthetic driving data generation has been used in prior research to emulate controlled driving behavior [22], real-world deployment introduces additional uncertainties such as sensor latency variability and environmental disturbances. Therefore, hardware-in-the-loop testing and physical sensor validation are necessary to confirm real-time stability and robustness under practical operating conditions.

Overall, these findings suggest that system-level architectural integration rather than isolated model sophistication plays a decisive role in reducing fragmentation within intelligent vehicle safety systems. The AI-MIMO supervisory framework provides a structured foundation for coordinated multi-output assistance while maintaining computational efficiency and scalability.

Conclusion

This study demonstrates that the proposed AI-MIMO architecture can effectively integrate multiple driving inputs into a unified and coordinated safety assistance system, fulfilling the research objectives. The results highlight that MIMO-based fusion with lightweight AI enables coherent decision-making using low-cost, independent sensors, advancing beyond fragmented conventional ADAS approaches. Although limited to simulation, this work provides a foundational contribution for developing scalable and affordable intelligent vehicle safety systems, with future research directed toward real-world and embedded validation.

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