Motive

AI model development

Applying the power of AI to save lives.

Summary

This guide explains Motive's unique approach to designing highly accurate and reliable AI features to save lives. Learn how our first-principles approach helps businesses be safer on the road.

- Unique model design
- Edge performance
- Long-tail scenario capture
- Iteration and deployment

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AI model development

Motive has developed a unique approach to creating AI models that save lives.

Our four-step AI model development process:

1 Model design

We analyze unsafe driving behaviors, then develop models to detect and prevent these practices. We push the boundaries and invent new methods as needed.

2 Edge performance

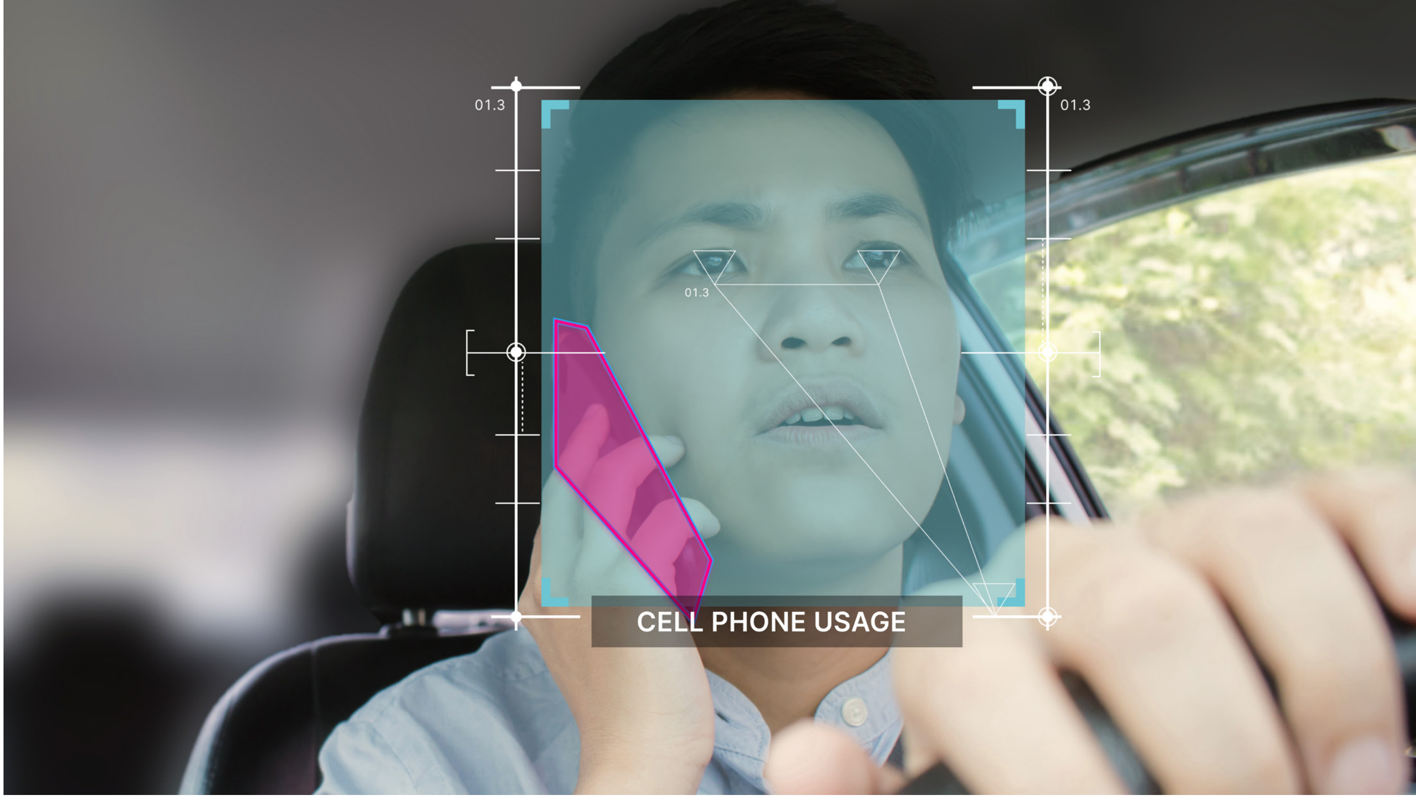
We port these models to the edge devices to accurately detect high-risk behaviors in real time.

3 Long-tail scenario capture

Once deployed in the field, we monitor performance with our extensive data loop to prioritize development.

4 Iteration and deployment

We use insights and data to roll out new and improved models every week.



Model design

We use a multi-task learning approach that improves learning efficiency and prediction accuracy. This approach creates a more flexible and scalable way of building AI models.

Cell phone usage

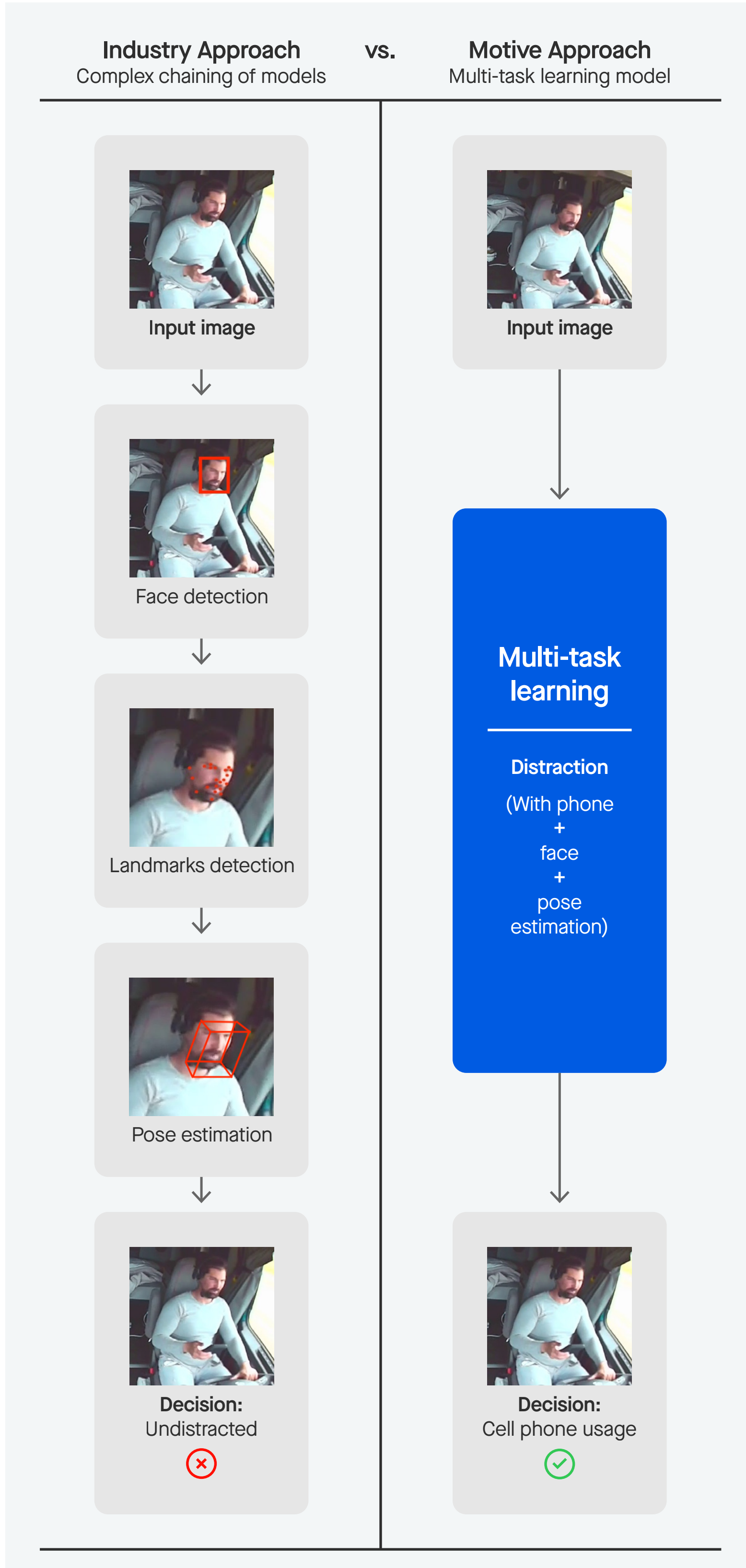
Most other third-party technology vendors use a complex chaining of models to detect distraction. This standard approach appears to only work in minimal, unrealistic situations, such as when the camera is installed directly in front of the driver and the lighting conditions are exceptional.

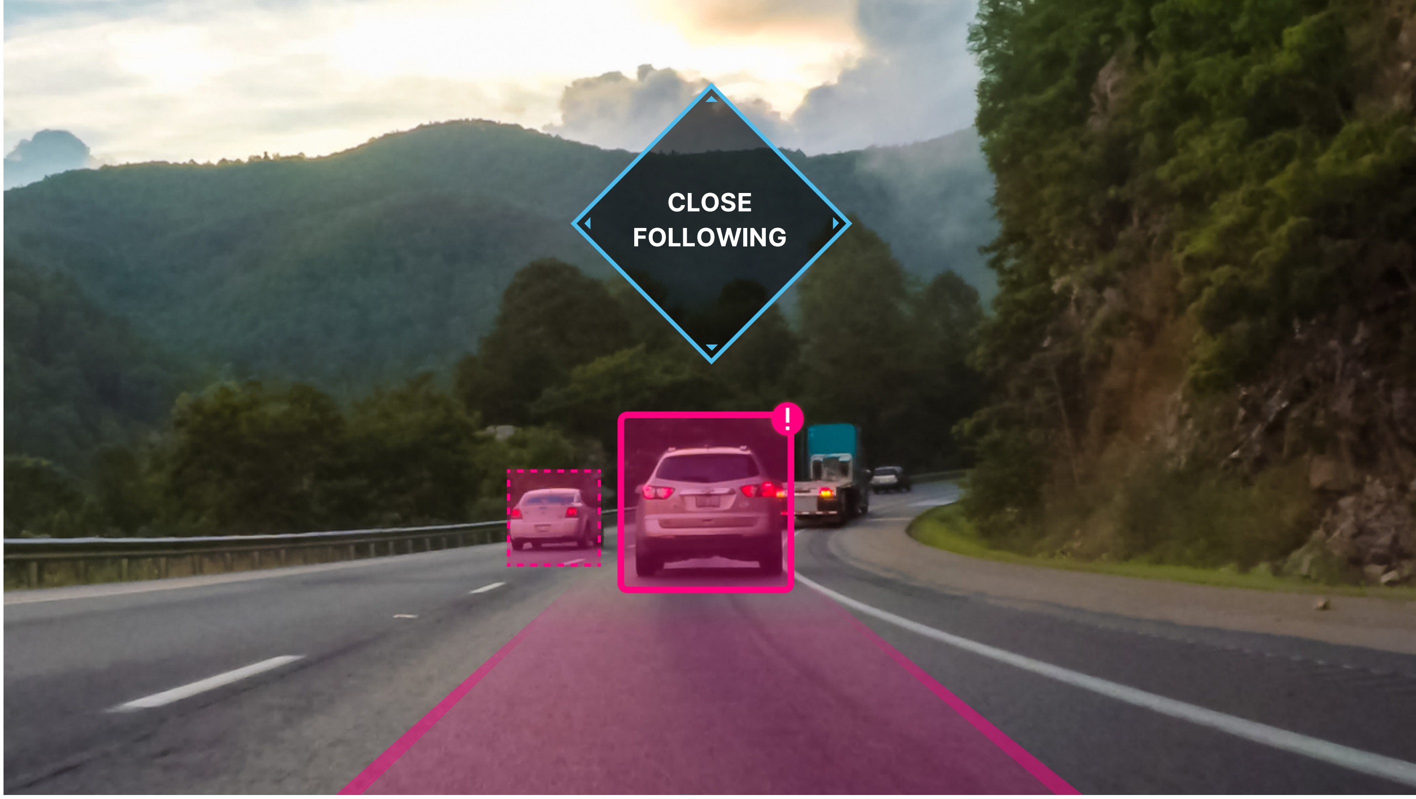
Standard models have accuracy issues and aren't efficient for edge devices. They also have multiple points of failure, and can't be extended to solve more complex problems.

We decided to go beyond standard models to make cell phone usage more reliable and efficient by using a novel multi-task learning approach. With multi-task learning, we can simultaneously solve multiple learning tasks and exploit commonalities and differences across the tasks. This approach for model training improves learning efficiency and prediction accuracy, compared to training the models separately.

Our multi-task model uses body pose and cell phone presence information to determine if the driver is using a phone. Instead of designing hard constraints for the model, we created a framework for AI to learn the relationship between different objects and events. For example, during training, the model learns the driver's typical pose and the location of their phone and face when they're distracted vs. when they're not. This model is a much more flexible and scalable way of building AI models.

Using our multi-task learning approach, our cell phone usage model is more accurate, better performing, and easily extendable.



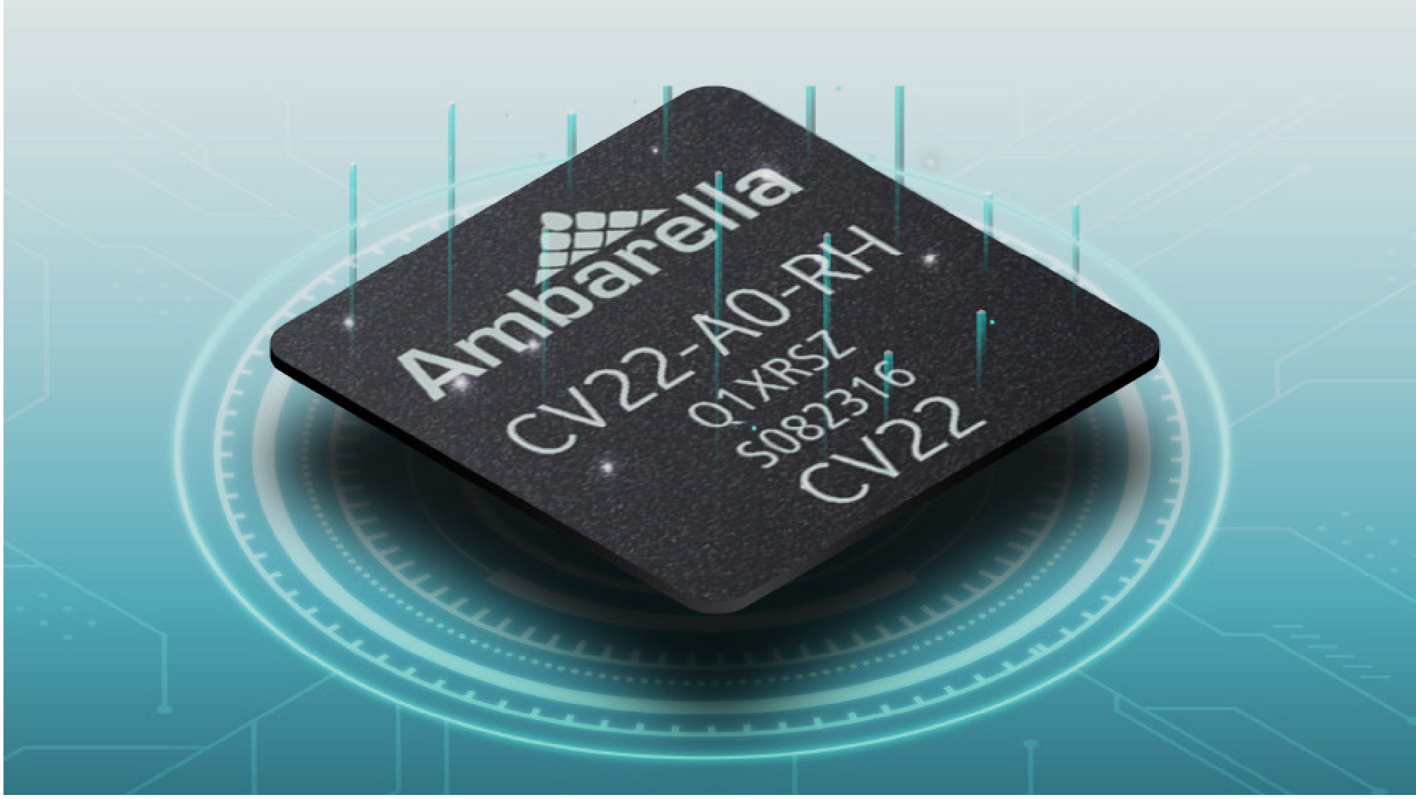


Close following

For close-following detection, we applied the same multi-task learning approach and validated its accuracy in several ways:

- **Industry research publications**
  Top computer vision and AI researchers have vetted our **distance estimation** and **lane detection** approaches.
- **Self-driving benchmarks**
  We tested our distance estimation on public self-driving car data sets, where it outperformed state-of-the-art distance estimation algorithms.
- **Patents**
  Our end-to-end close-following approach is patent pending.

We're applying our multi-task learning approach to detect many other unsafe behaviors that cause accidents — such as rolling stops, seat belt violations, drowsiness, and more.



Edge performance

We run robust AI models that maximize hardware performance, thanks to our powerful AI processor and rigorous porting and deployment process.

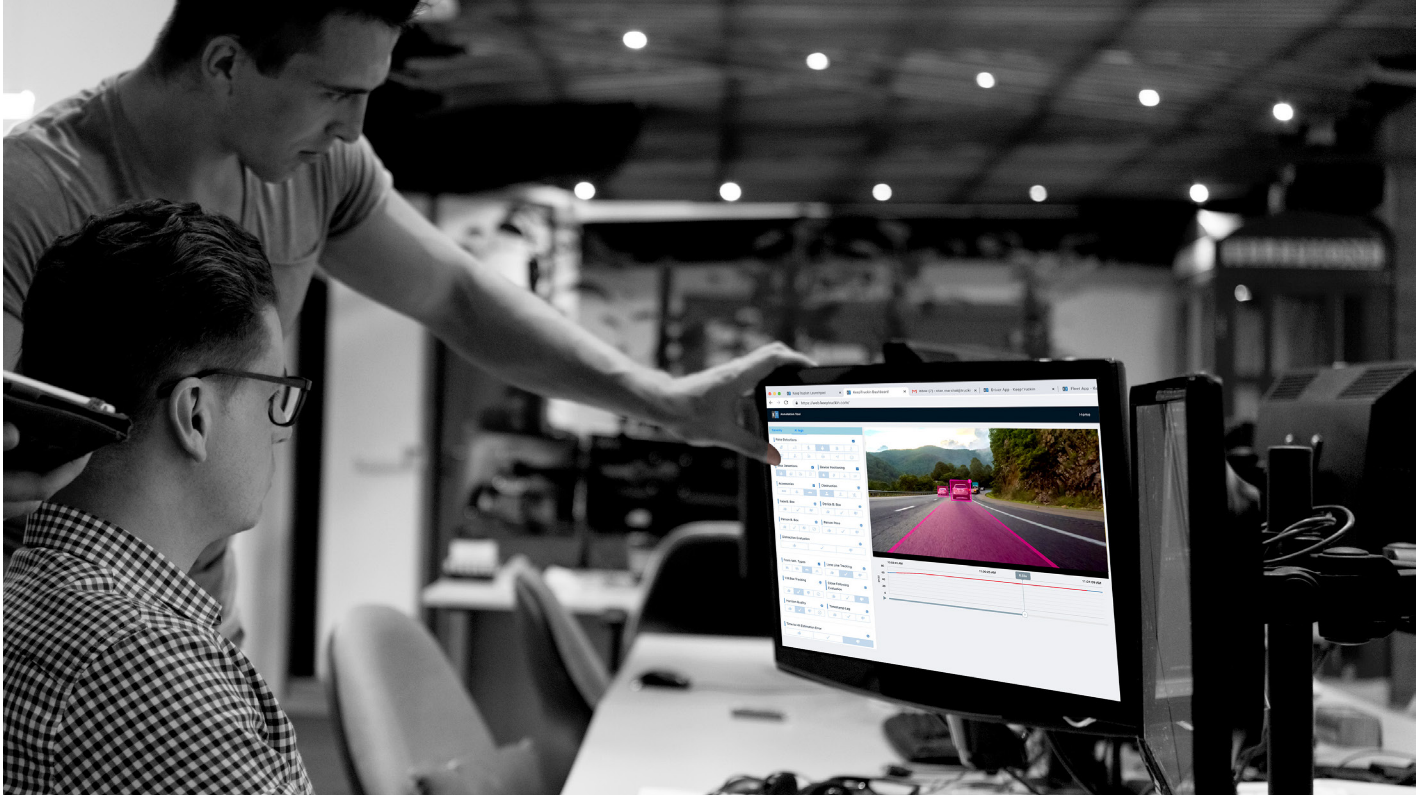
The Ambarella CV22 processor in our AI Dashcam provides a powerful, cost-effective, and efficient platform to build on. Additionally, we employ a rigorous porting and deployment process that optimizes the model for the best performance on the hardware.

Porting is a multi-step, iterative process to reduce neural network size by dropping insignificant neurons and reducing the floating-point precision. During network pruning and quantizing, we ensure that the edge model's output matches the output of the server model, and the difference between their output confidence is less than 3%.

Below are results of our recent model porting validation. In all cases, the difference between the edge and cloud model's confidence output is well within our acceptable range.

Difference between edge and cloud model confidence output

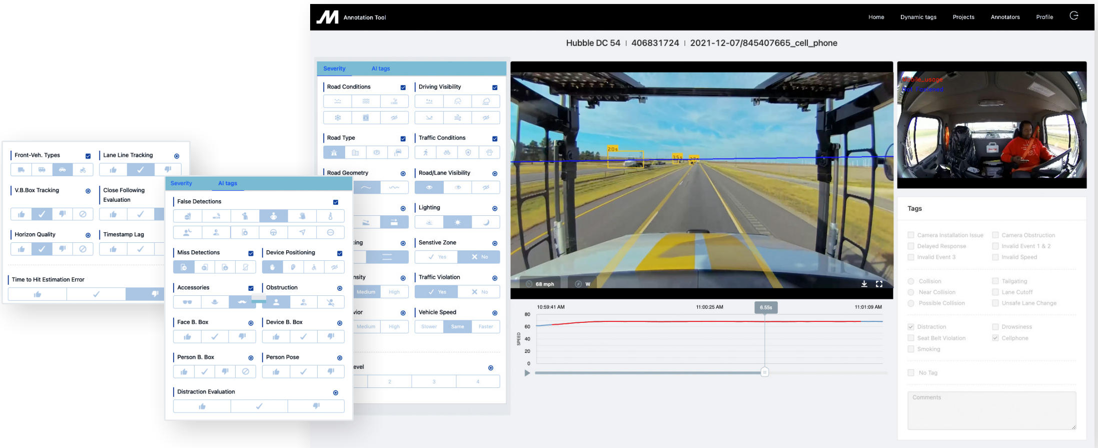
Test set	Distraction	Seat belt
1	-0.12%	-0.38%
2	0.80%	0.10%
3	0.00%	-2.10%
4	1.70%	0.00%



Long-tail scenario capture

Our in-house safety team reviews and labels every video to capture as many long-tail scenarios as possible. These contextual tags help improve the accuracy of our AI models.

Building commercially viable and accurate computer vision/AI products requires finding and solving the long tail of AI scenarios. Forward-looking AI companies, like Tesla, invest heavily in the annotation teams and infrastructure that help in this process. Our 300-person, in-house safety team operates 24/7, 365 days per year. They label every collected video to capture as many scenarios as possible, so we can continuously train and improve our models.



Annotation interface used to review videos for AI model performance and scenario information.

We've invested heavily in building real-time pipelines and processes to find failure scenarios. Our annotation process generates detailed information on model performance and scenario information like time of day, road type, weather, etc.

We aggregate the data collected through this extensive annotation process to drive our AI model development roadmap. We use this data to identify common driving patterns when events occur and calculate the accuracy for each scenario identified by the AI model. By combining frequency with precision, we can then prioritize the scenarios, such as ones with potential false negatives.

The table below shows aggregated field data for our close-following detection. Using this data, we identified issues and improved performance on the low light and curved road scenarios. Additionally, since there are fewer low light/nighttime events, one can infer a false negative issue in those cases. We were able to disprove that by analyzing the drive-time trends for vehicles on our network.

Aggregated field data for close-following detection

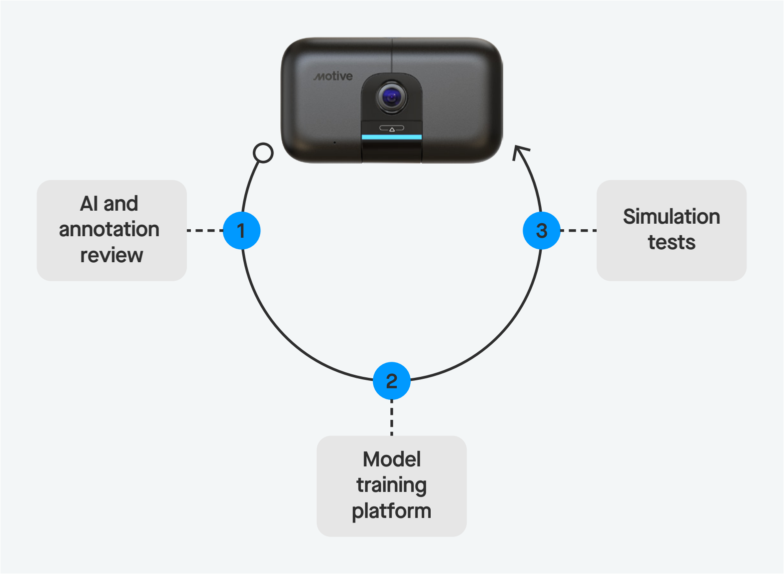
Time of day	Road type	Road geometry	True positive	False positive	Total	Occurrence	Field precision
Daytime	Highway	Straight	10,593	930	11,523	57.47%	**91.93%**
		Slightly Curved	3,139	392	3,531	17.61%	**88.90%**
	City	Straight	1,009	103	1,112	5.55%	**90.74%**
Twilight	Highway	Straight	787	106	893	4.45%	**88.13%**
Night	Highway	Straight	750	89	839	4.18%	**89.39%**

Measuring false negatives is inherently challenging. We use our video and telematics data points to build a vast backtest dataset, which is run through cloud models to estimate false negatives.

Iteration and deployment

Through rapid iteration and constant updating, we constantly improve our ability to predict where risk lies.

We apply the insights generated by our in-house safety team to our AI infrastructure to retrain models and deploy weekly updates to the field.



AI and annotation review

Our extensive annotation process helps identify challenging scenarios that yield the highest return on investment for feature improvement. We focus on those scenarios and leverage the insights for future model training and improvements.

Model training platform

Many AI companies struggle with the number of concurrent model experiments and deployment speed. However, with our investment in the end-to-end experimentation infrastructure, we can run multiple experiments and model updates every week. Some of our investments include:

- **Data pipelines**
  Automatic addition of new videos to our data store for future model training.
- **Training infrastructure**
  Single-click model training and comparison.

Simulation tests

We validate every new model before deploying it in the field. We use the safety team's model feedback and scenario data to curate thousands of videos used for model verification.

For reference, our recent lane and vehicle models for the close-following feature were validated in over 10,000 different videos.

Model	Road geometry	Videos	Precision	Recall	Accuracy
Vehicle model v2 Lane model v1	Straight	1,584	0.85	0.96	0.85
	Slightly curved	664	0.84	0.97	0.86
	Very curved	252	0.77	0.94	0.79
	Total	**2,500**	**0.84**	**0.96**	**0.85**
Vehicle model v3 Lane model v2	Straight	1,584	0.93	0.93	0.90
	Slightly curved	664	0.92	0.91	0.89
	Very curved	252	0.88	0.86	0.84
	Total	**2,500**	**0.93**	**0.92**	**0.89**

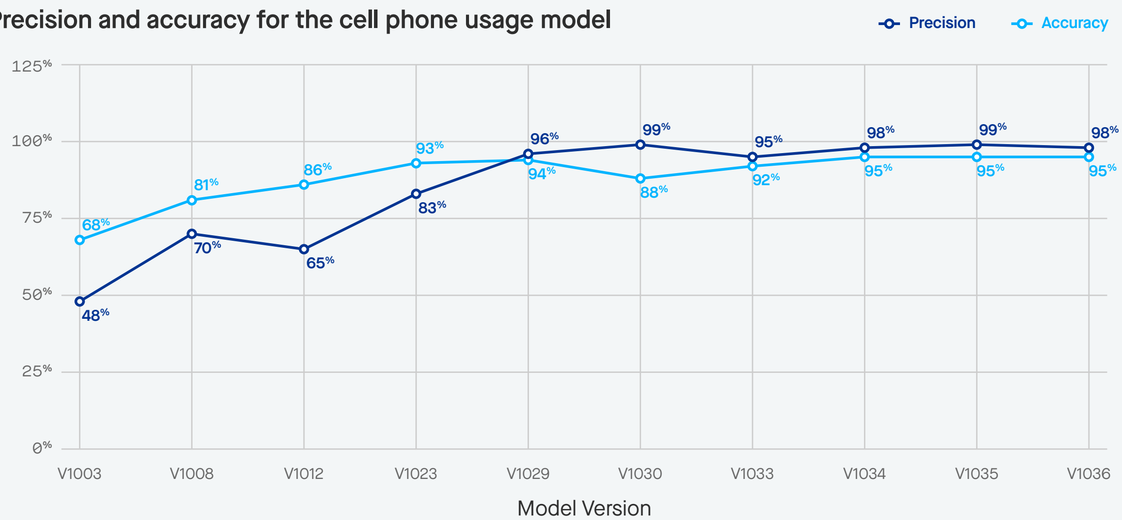
Deployment infrastructure

Once a new model is validated and ready for deployment, it goes through our Firmware Over-The-Air (FOTA) system to ensure secure, fast, and reliable deployment.

Updates for	Update time	Installation time	Downtime
 Vehicle Gateway	6–8 minutes	Within 3–5 minutes after the engine is off	2–3 minutes
 AI Dashcam	1–2 minutes	Within 10 minutes of download	~30 seconds

Using this process, we've collected thousands of videos and significantly improved our models' performance since launching the first model in beta. The graph shows the improvements in precision and accuracy of our cell phone usage model.

Precision and accuracy for the cell phone usage model



Conclusion

Through our first-principles approach to designing AI features, we've created a more accurate, reliable AI Dashcam and safety platform that can help prevent accidents, protect drivers, and lower costs.

Motive's four-step process helps us create AI features that set our technology apart and ultimately save lives on the road.

Unlock Potential

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About Motive

Motive builds technology to improve the safety, productivity, and profitability of businesses that power the physical economy. The Motive Automated Operations Platform combines IoT hardware with AI-powered applications to automate vehicle and equipment tracking, driver safety, compliance, maintenance, spend management, and more. Motive serves more than 120,000 businesses, across a wide range of industries including trucking and logistics, construction, oil and gas, food and beverages, field services, agriculture, passenger transit, and delivery. Visit **gomotive.com** to learn more.

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