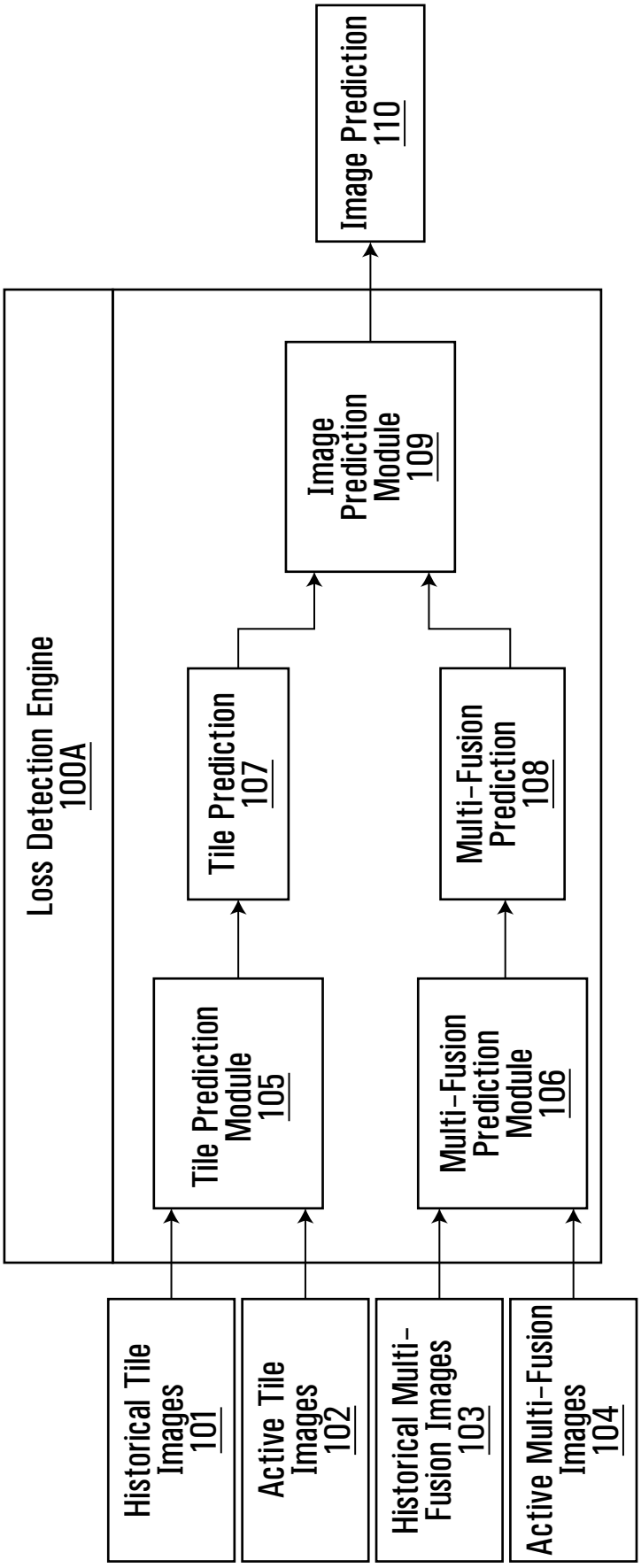
Historical Tile Images 101
Active Tile Images 102
Historical Multi-Fusion Images 103
Active Multi-Fusion Images 104
Loss Detection Engine 100A
Tile Prediction Module 105
Multi-Fusion Prediction Module 106
Tile Prediction 107
Multi-Fusion Prediction 108
Image Prediction Module 109
Image Prediction 110

FIG. 1

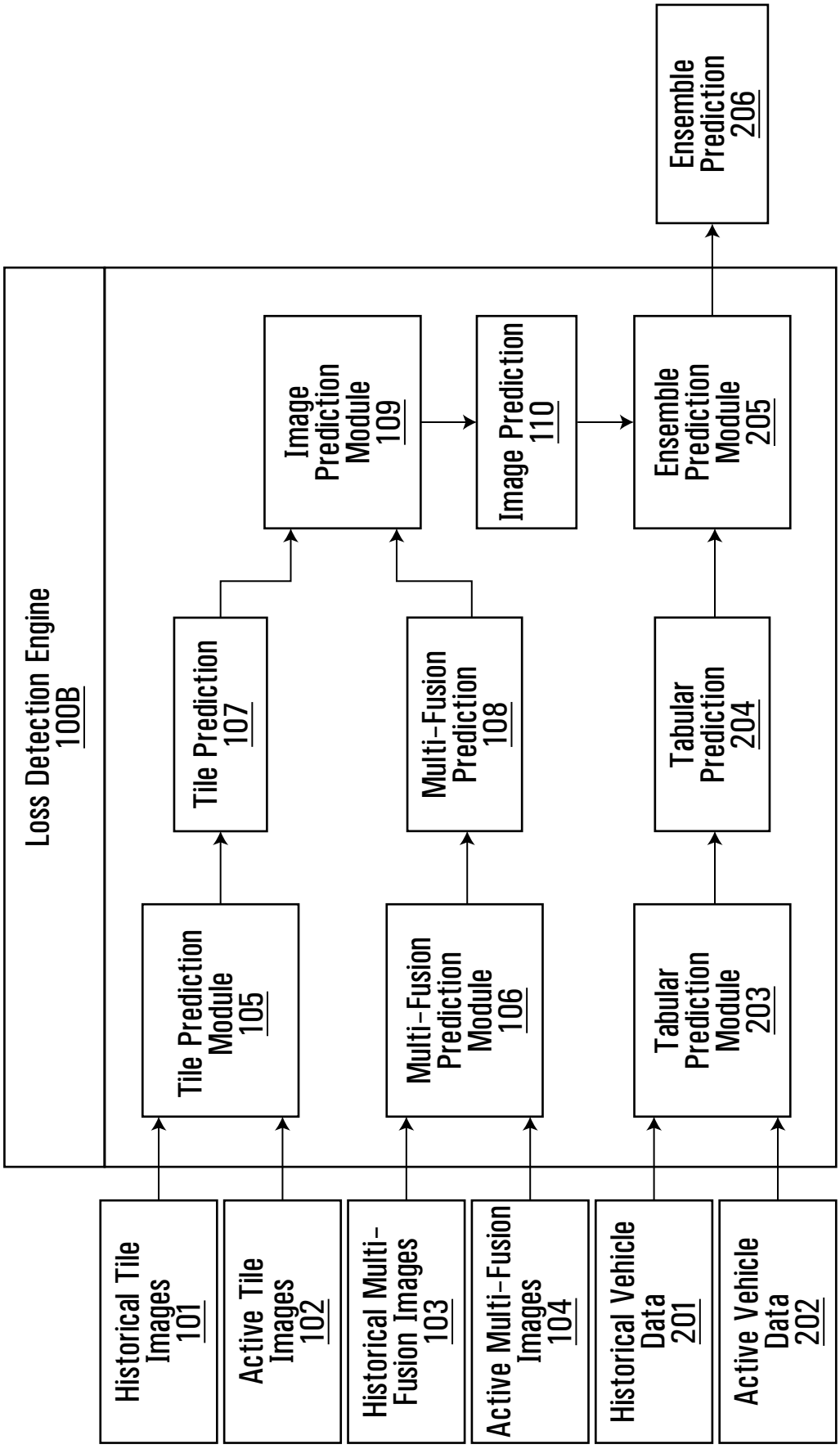
Loss Detection Engine
100B
Historical Tile Images
101
Active Tile Images
102
Historical Multi-Fusion Images
103
Active Multi-Fusion Images
104
Historical Vehicle Data
201
Active Vehicle Data
202
Tile Prediction Module
105
Multi-Fusion Prediction Module
106
Tabular Prediction Module
203
Tile Prediction
107
Multi-Fusion Prediction
108
Tabular Prediction
204
Image Prediction Module
109
Image Prediction
110
Ensemble Prediction Module
205
Ensemble Prediction
206

FIG. 2

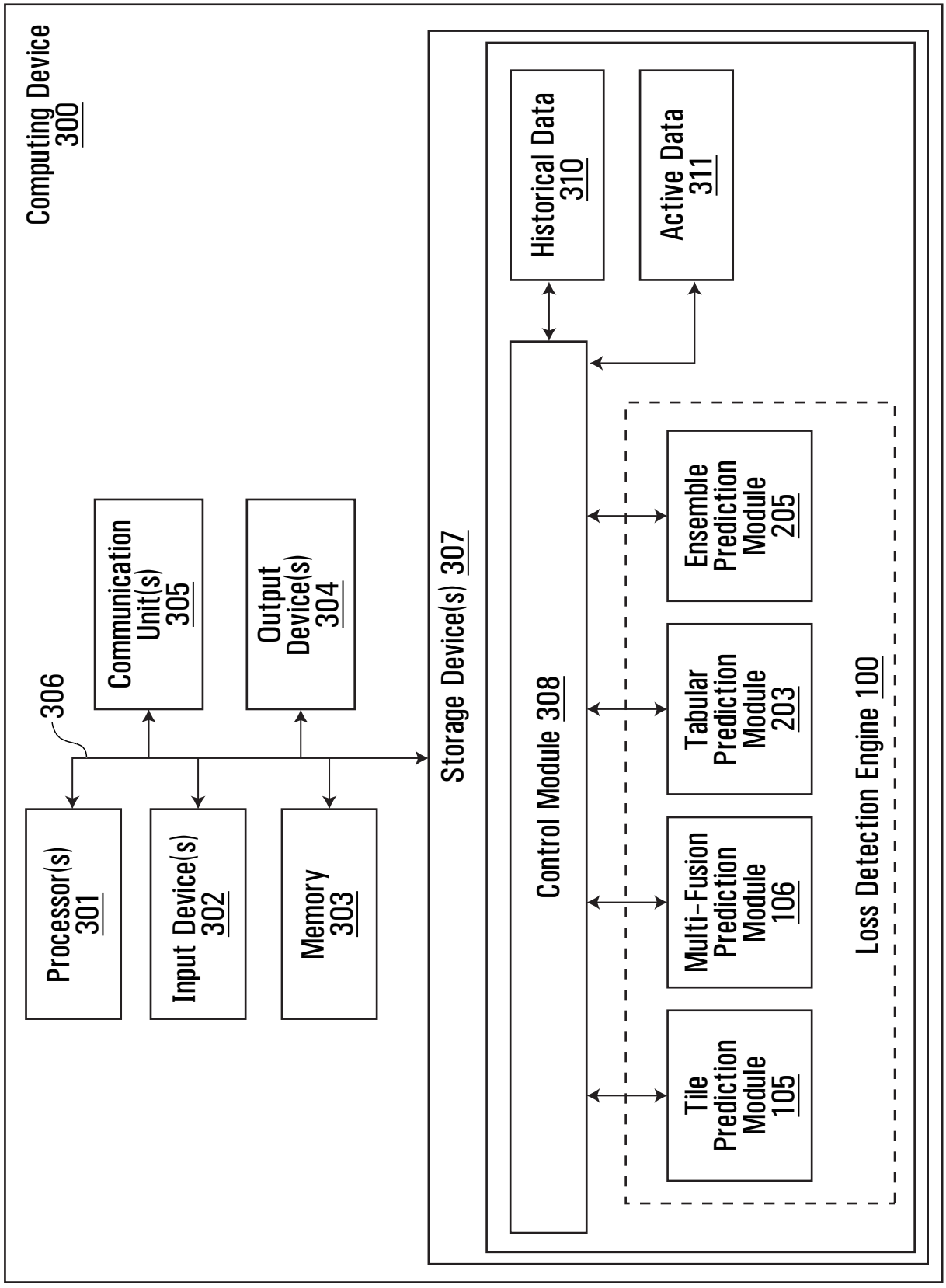
Computing Device 300
Processor(s) 301
Input Device(s) 302
Memory 303
306
Communication Unit(s) 305
Output Device(s) 304
Storage Device(s) 307
Historical Data 310
Active Data 311
Control Module 308
Tile Prediction Module 105
Multi-Fusion Prediction Module 106
Tabular Prediction Module 203
Ensemble Prediction Module 205
Loss Detection Engine 100

FIG. 3

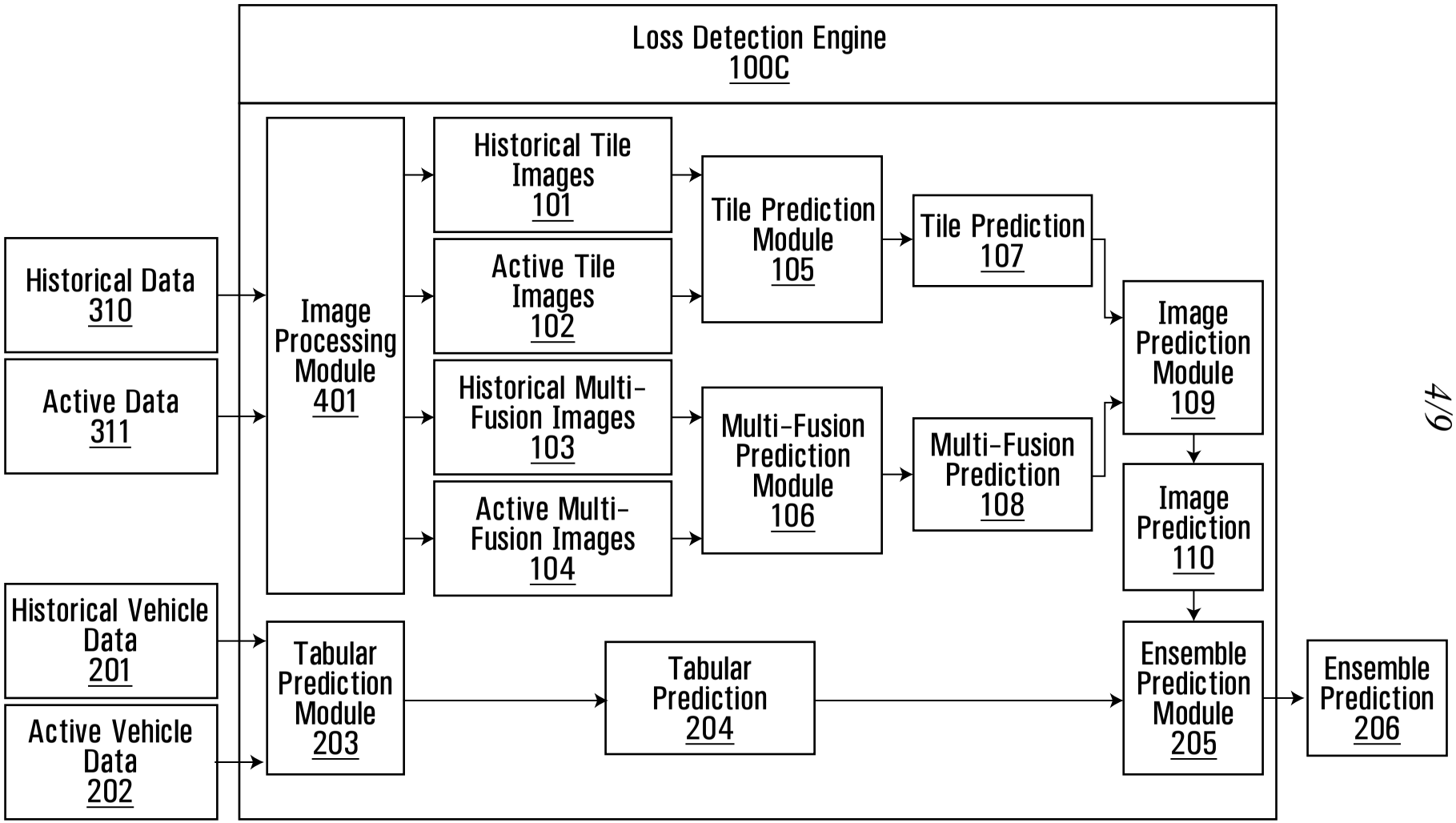
Loss Detection Engine
100C
Historical Data
310
Active Data
311
Historical Vehicle Data
201
Active Vehicle Data
202
Image Processing Module
401
Historical Tile Images
101
Active Tile Images
102
Historical Multi-Fusion Images
103
Active Multi-Fusion Images
104
Tile Prediction Module
105
Multi-Fusion Prediction Module
106
Tile Prediction
107
Multi-Fusion Prediction
108
Image Prediction Module
109
Image Prediction
110
Tabular Prediction Module
203
Tabular Prediction
204
Ensemble Prediction Module
205
Ensemble Prediction
206

FIG. 4

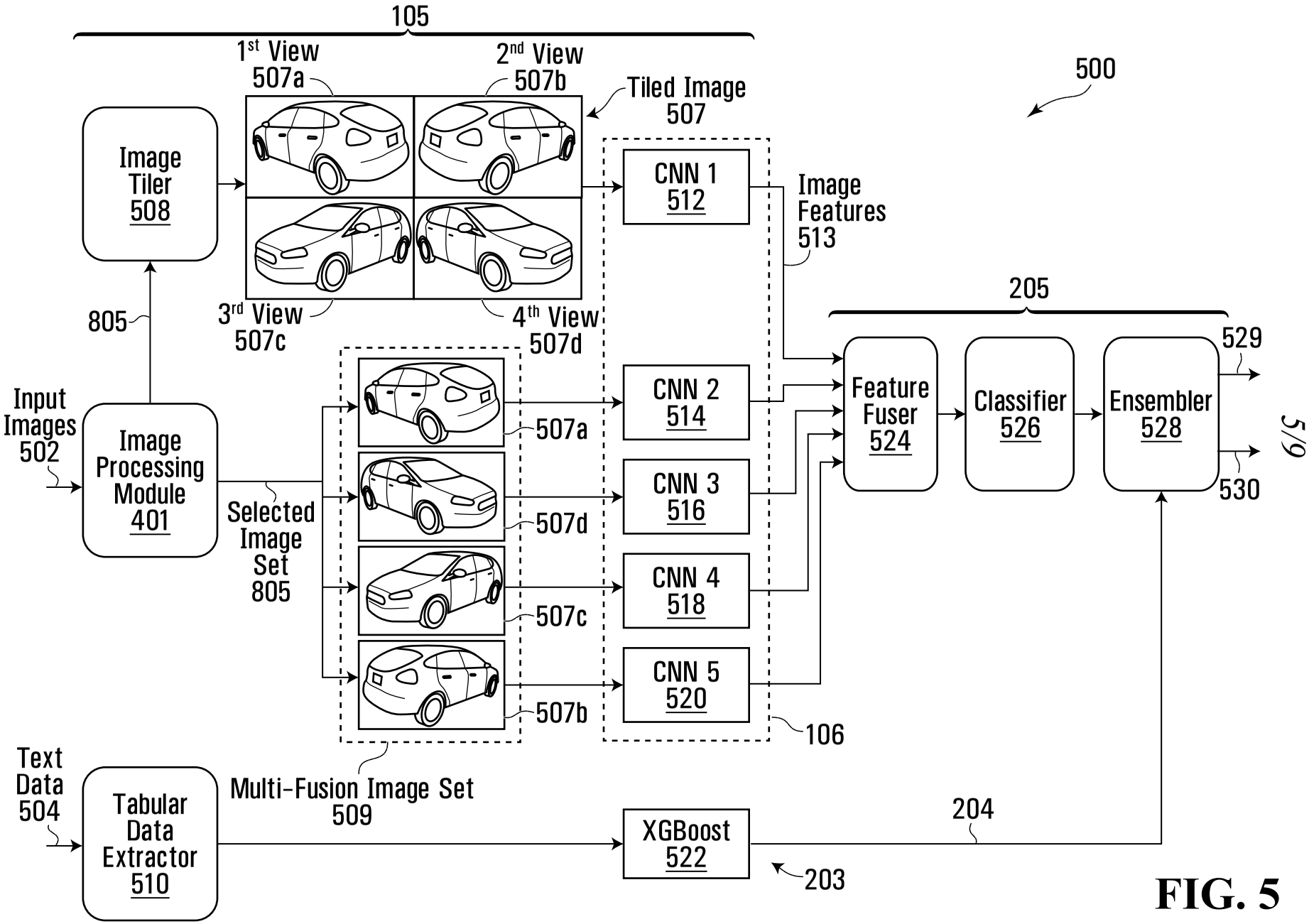
105
1st View
507a
2nd View
507b
Tiled Image
507
500
Image
Tiler
508
CNN 1
512
Image
Features
513
205
805
3rd View
507c
4th View
507d
529
Input
Images
502
Image
Processing
Module
401
Selected
Image
Set
805
507a
CNN 2
514
Feature
Fuser
524
Classifier
526
Ensembler
528
507d
CNN 3
516
530
507c
CNN 4
518
507b
CNN 5
520
106
Text
Data
504
Tabular
Data
Extractor
510
Multi-Fusion Image Set
509
XGBoost
522
204
203
5/9

FIG. 5

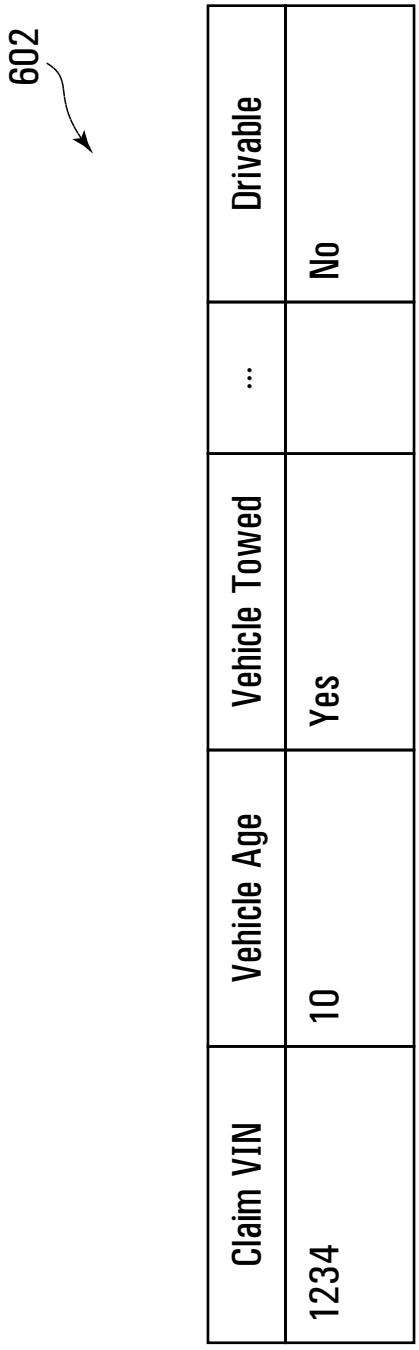
602
Claim VIN
Vehicle Age
Vehicle Towed
...
Drivable
1234
10
Yes
No

FIG. 6

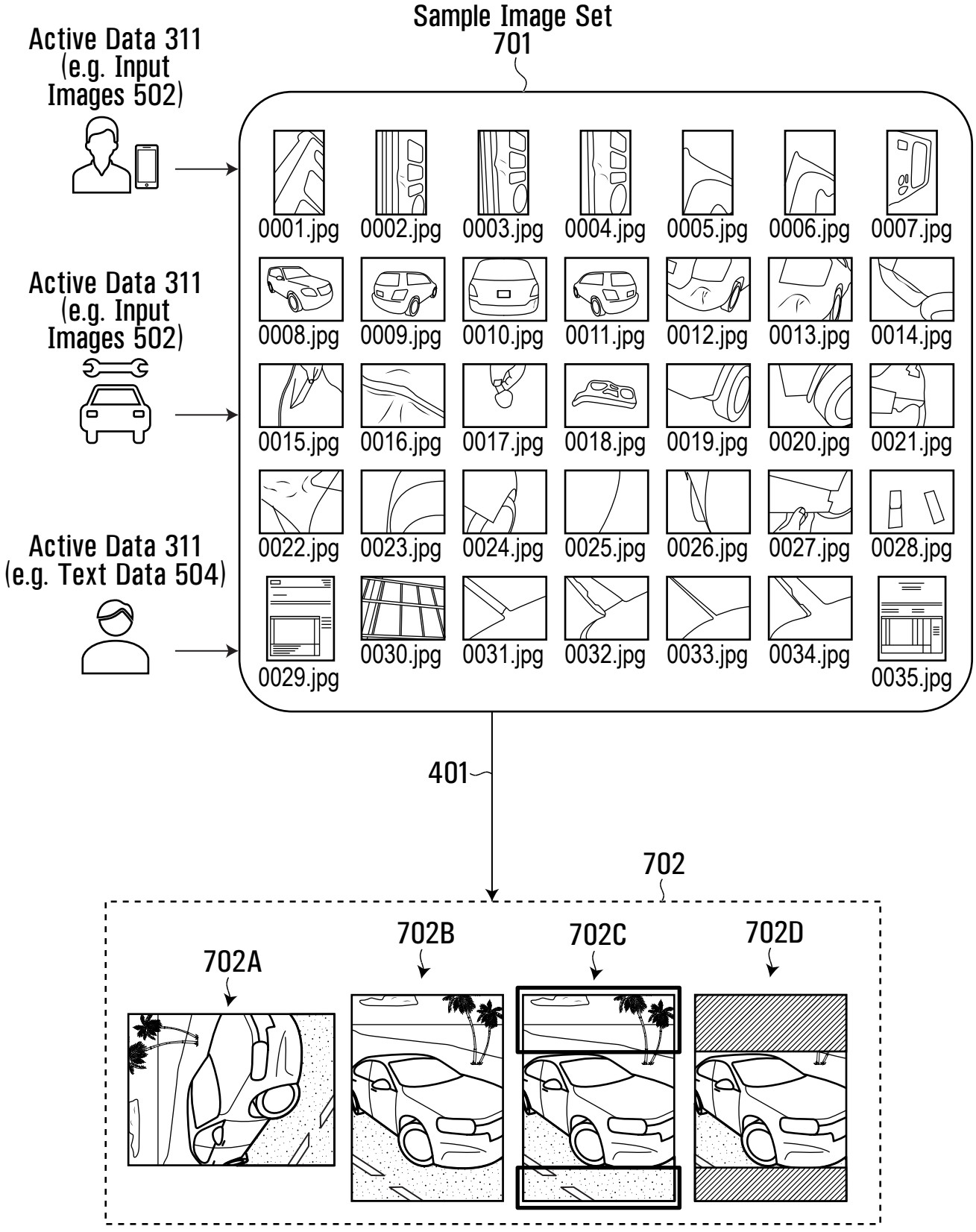
Sample Image Set
701
Active Data 311
(e.g. Input
Images 502)
Active Data 311
(e.g. Input
Images 502)
Active Data 311
(e.g. Text Data 504)
0001.jpg
0002.jpg
0003.jpg
0004.jpg
0005.jpg
0006.jpg
0007.jpg
0008.jpg
0009.jpg
0010.jpg
0011.jpg
0012.jpg
0013.jpg
0014.jpg
0015.jpg
0016.jpg
0017.jpg
0018.jpg
0019.jpg
0020.jpg
0021.jpg
0022.jpg
0023.jpg
0024.jpg
0025.jpg
0026.jpg
0027.jpg
0028.jpg
0029.jpg
0030.jpg
0031.jpg
0032.jpg
0033.jpg
0034.jpg
0035.jpg
401
702
702A
702B
702C
702D

FIG. 7

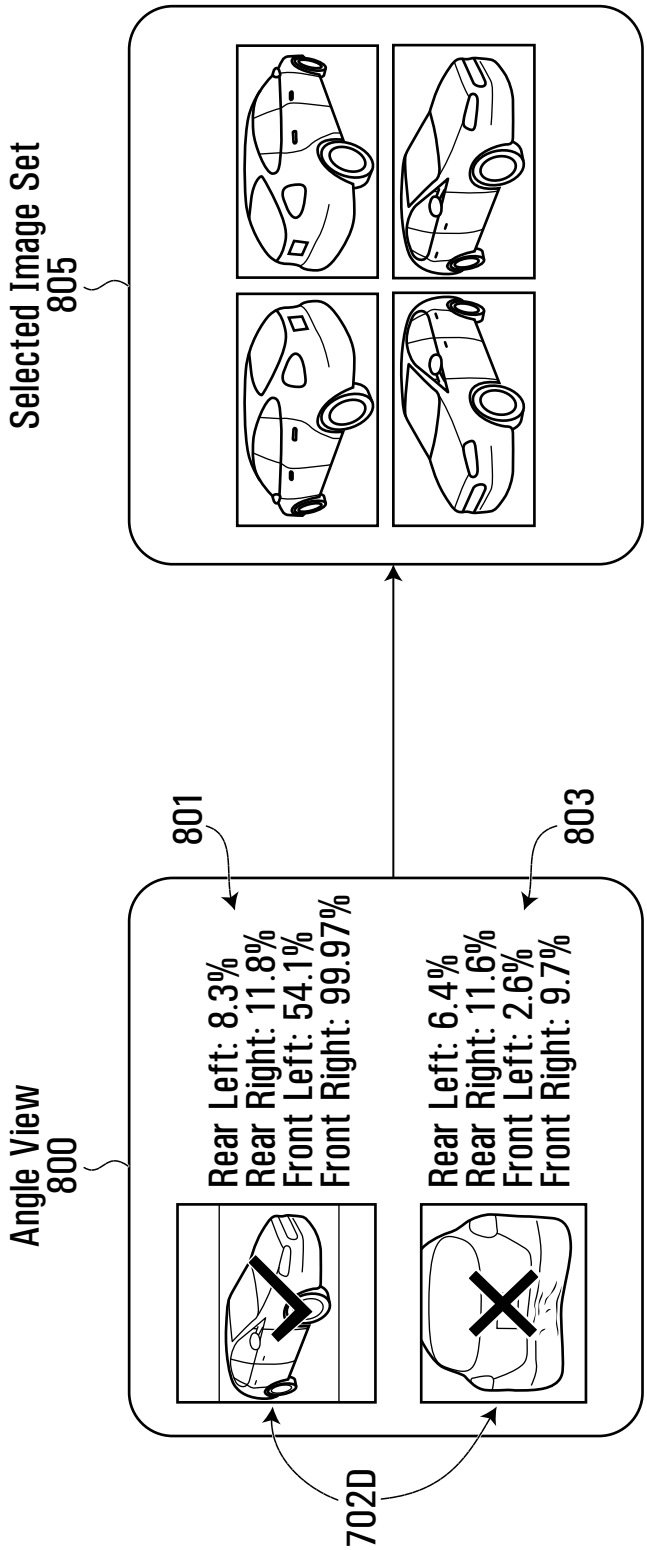
Selected Image Set
805
Angle View
800
801
803
Rear Left: 8.3%
Rear Right: 11.8%
Front Left: 54.1%
Front Right: 99.97%
Rear Left: 6.4%
Rear Right: 11.6%
Front Left: 2.6%
Front Right: 9.7%
702D

FIG. 8

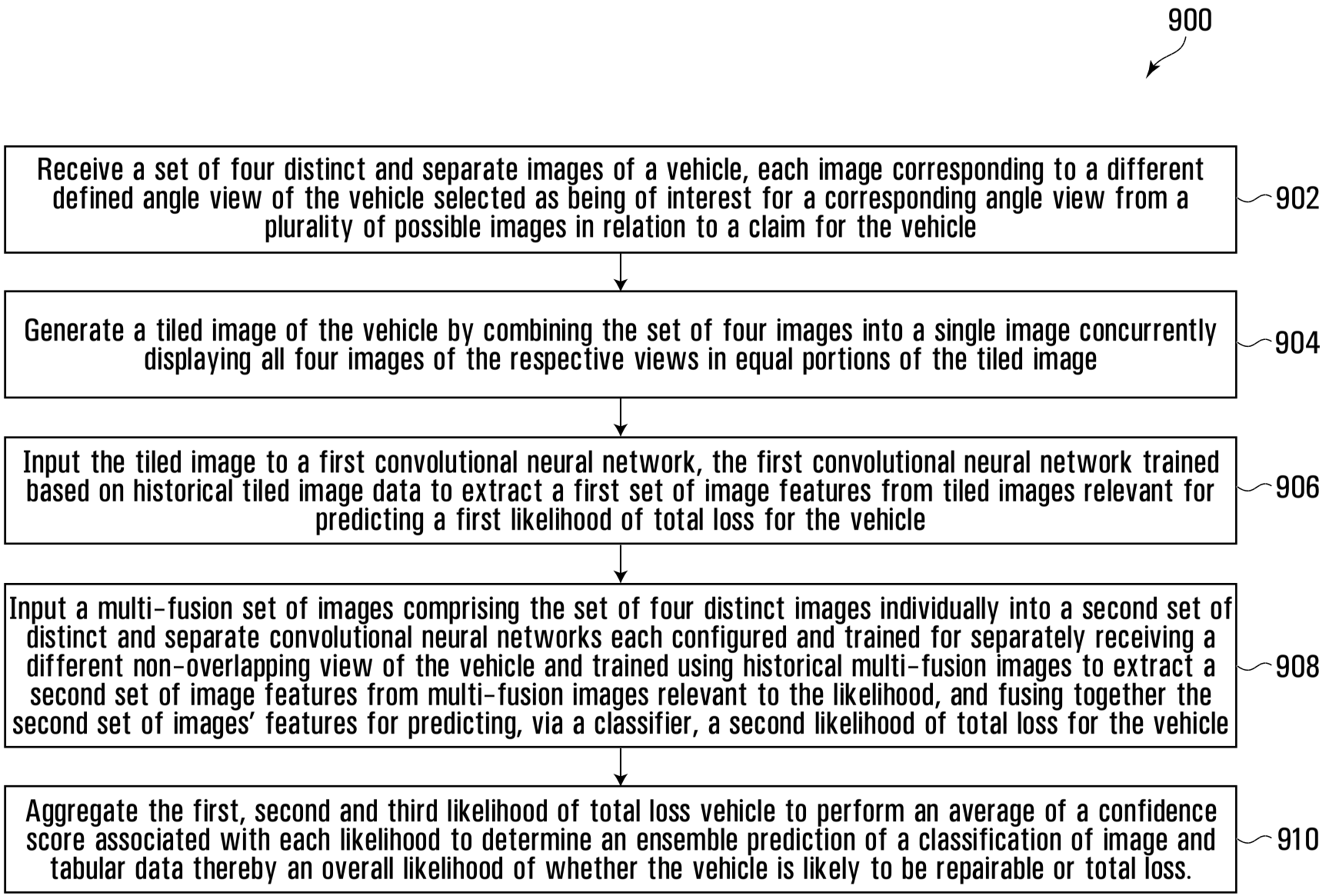
900
Receive a set of four distinct and separate images of a vehicle, each image corresponding to a different defined angle view of the vehicle selected as being of interest for a corresponding angle view from a plurality of possible images in relation to a claim for the vehicle
902
Generate a tiled image of the vehicle by combining the set of four images into a single image concurrently displaying all four images of the respective views in equal portions of the tiled image
904
Input the tiled image to a first convolutional neural network, the first convolutional neural network trained based on historical tiled image data to extract a first set of image features from tiled images relevant for predicting a first likelihood of total loss for the vehicle
906
Input a multi-fusion set of images comprising the set of four distinct images individually into a second set of distinct and separate convolutional neural networks each configured and trained for separately receiving a different non-overlapping view of the vehicle and trained using historical multi-fusion images to extract a second set of image features from multi-fusion images relevant to the likelihood, and fusing together the second set of images' features for predicting, via a classifier, a second likelihood of total loss for the vehicle
908
Aggregate the first, second and third likelihood of total loss vehicle to perform an average of a confidence score associated with each likelihood to determine an ensemble prediction of a classification of image and tabular data thereby an overall likelihood of whether the vehicle is likely to be repairable or total loss.
910

FIG. 9