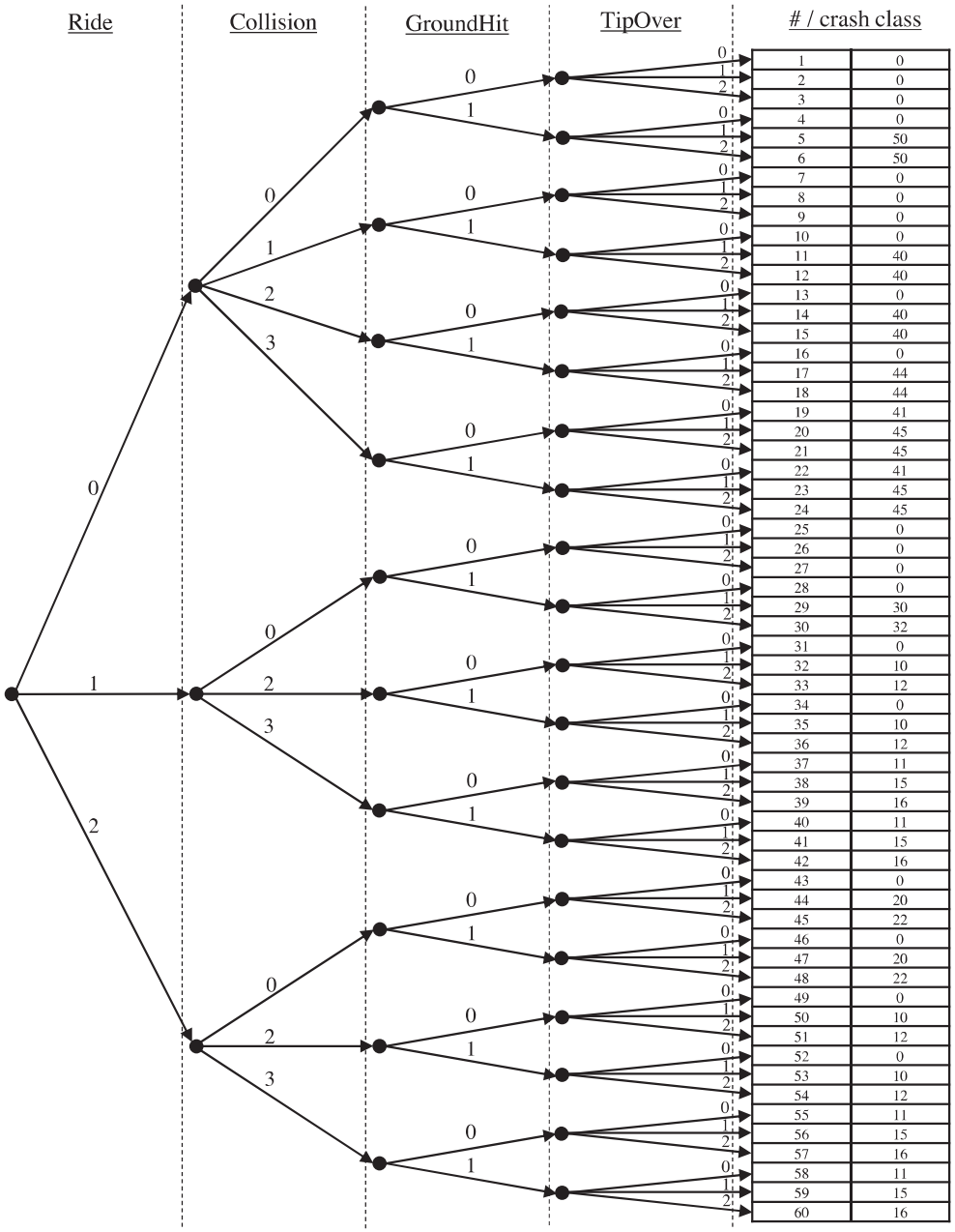
where $p(\mathbf{X})$ is the probability estimation of a binary feature, which can be interpreted as a confidence level. $\boldsymbol{\beta}$ is the corresponding hyper-parameter vector which is trained with input signals $\mathbf{X}$ of the training data (Hastie et al., 2001, p.119ff).

The defined crash features (see Table 1) are built based on separate logit models. This manual technique of defining and handling each crash feature separately is used due to the small amount of available crash data (see Section 3), where the most influencing input variables can be determined manually for each crash feature, to reduce model over-fitting. In Section 2.4, the approach for combining all logit models is presented. It is noted that the method of logistic regression is enhanced by the k-fold cross validation and lasso regularization for selecting optimal training data and to further reduce over-fitting onto the training data (Hastie et al., 2001, p.241ff; Algamal and Lee, 2015).

2.4. Feature combination

After treating the crash features separately (see Section 2.5), a probabilistic decision tree is constructed to analyze the combining effect of the crash feature models, as shown in Fig. 3. These features are defined as stochastically independent probabilistic models, thus the shown decision tree presents all possible feature state combinations (except for C1 soft collisions, which cannot be distinguished during Rd1/Rd2 riding situations from general intense vibrations and therefore are consequently treated as C0 no collisions). This procedure leads to 60 kinematic output classes. We merge all 60 output scenarios into super-crash and sub-crash classes according to their similarities in the kinematic trajectories. If an event responds to the output with the crash class of '0', the corresponding kinematic scenario will not be defined as a bicycle accident.

We distinguish the combined scenarios with similar kinematic trajectories into 5 merged super-crash classes (i.e., 1X-5X), as shown in



#	crash class
1	0
2	0
3	0
4	0
5	50
6	50
7	0
8	0
9	0
10	0
11	40
12	40
13	0
14	40
15	40
16	0
17	44
18	44
19	41
20	45
21	45
22	41
23	45
24	45
25	0
26	0
27	0
28	0
29	30
30	32
31	0
32	10
33	12
34	0
35	10
36	12
37	11
38	15
39	16
40	11
41	15
42	16
43	0
44	20
45	22
46	0
47	20
48	22
49	0
50	10
51	12
52	0
53	10
54	12
55	11
56	15
57	16
58	11
59	15
60	16

Fig. 3. Structure of decision tree for bicycle crash classification, including merged (super and sub) output crash classes.