

## SUPPLEMENTARY DATA

### ADMETLAB 3.0: AN UPDATED COMPREHENSIVE ONLINE ADMET PREDICTION PLATFORM ENHANCED WITH BROADER COVERAGE, IMPROVED PERFORMANCE, API FUNCTIONALITY, AND DECISION SUPPORT

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## DMPNN framework

Yang et al (1). introduced an open-source Python package called Chemprop designed for implementing DMPNN models. This package offers a robust and efficient solution tailored for molecular property prediction tasks and has garnered extensive utilization in fields such as drug discovery and materials science (2). Within the DMPNN framework, there exist two distinct stages: message passing and readout. Here, a graph  $G$  serves as an illustrative example, representing node (atom) features as  $x_v$  and edge (bond) features as  $e_{vw}$ . Initially, the edge hidden state  $h_{vw}^0$  is initialized using eq 1. This equation concatenates atom and bond features by passing them through the learned matrix  $W_l$  and applying the rectified linear unit (RELU) activation function. This initialization defines the edge hidden state, which undergoes subsequent updates during the message passing process. In eq 1,  $\tau$  represents the RELU activation function,  $W_l$  denotes a learned matrix, and  $cat()$  signifies a basic concatenation operation.

$$h_{vw}^0 = \tau(W_l cat(x_v, e_{vw})) \quad (1)$$

The first phase of message passing computes interactions between atom  $v$  and atom  $w$ . This is achieved by summing the hidden states of all bonds connected to atom  $v$  while excluding the hidden state of bonds from atom  $w$ , as described by  $m_{vw}^{t+1}$  in eq 2. This step captures information about the neighboring atoms and their connections to individual atoms within  $vw$ . In eq 2,  $h_{kv}^t \in R^D$  represents bond features at layer  $t \in \{1, 2, \dots, T\}$ ,  $k \in \{N(v) \setminus w\}$  denotes the set of nodes connected to  $v$  excluding  $w$ .

$$m_{vw}^{t+1} = \sum_{k \in \{N(v) \setminus w\}} h_{kv}^t \quad (2)$$

Following this, a new hidden message at depth 1 is created by summing the product of the initial hidden state and the learned matrix  $W_m$  with the message. This resultant output undergoes further processing using the activation function  $\tau$ , denoted as  $h_{vw}^{t+1}$  in eq 3.

$$h_{vw}^{t+1} = \tau(h_{vw}^0 + W_m m_{vw}^{t+1}) \quad (3)$$

In the final message passing layer (at  $t=T$ ), the updated hidden states  $h_{vw}^T$  are summed to create the ultimate message for each atom, as described in eq 4. This action aggregates information about all neighboring atoms and their relationships into the final message for each atom.

$$m_v = \sum_{w \in N(v)} h_{vw}^T \quad (4)$$

The hidden state  $h_v$  for each atom is derived by concatenating the initial atom features with the message vector, as indicated in eq 5.

$$h_v = \tau(W_i \text{cat}(x_v, m_v)) \quad (5)$$

Finally, employing eq 6, the hidden states  $h_v$  of each atom are summed to generate a molecular feature vector. This step aggregate information from all atoms in the molecule into a unified molecular feature vector, facilitating property prediction. It encompasses both structural and attribute information of the entire molecule, offering a comprehensive representation for further property prediction.

$$h = \sum_{v \in N(v)} h_v \quad (6)$$

In the DMPNN-Des model, preceding the readout phase, vector  $h$  is concatenated with descriptor vectors and collectively processed using a fully connected feedforward neural network to predict properties. The algorithm is implemented using the open-source Chemprop package (2). Regarding the raw datasets, we trained each dataset using Chemprop, employing random segmentation ratios [0.8, 0.1, 0.1] for training, testing, and evaluation. The batch process is iterated five times, and the average RMSE value and variance from these iterations are calculated to evaluate the robustness of the model.

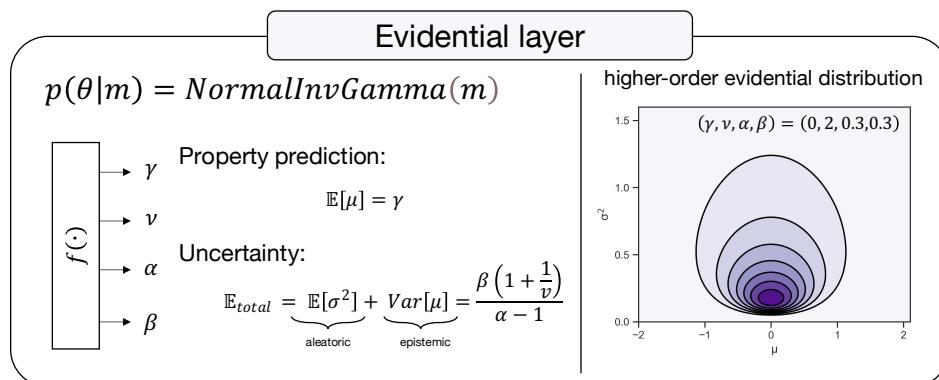
## Uncertainty estimation method

In pharmaceutical research, especially in ADMET assessment, unreliable predictions might lead to misjudging drug efficacy, causing missed opportunities in drug development. Therefore, within AI-assisted drug development, quantifying predictive reliability is crucial for guiding subsequent research decisions by medicinal chemists (3).

### Regression model

Within the regression model, ADMETlab 3.0 employs the evidence-based deep learning technique proposed by Amini et al (4). Evidential deep learning extends the concept of learning probability distribution parameters, further predicting higher-order distributions of the original likelihood parameters themselves. These higher-order parameters define the evidence distribution, thereby capturing the model's predictions and the degree of evidence associated with those predictions. In contrast to Bayesian neural networks that set priors on neural network weights, the evidence learning approach estimates uncertainty by directly learning the parameters defining this evidence distribution. It encompasses both epistemic and aleatoric uncertainties, eliminating the need for sampling and thus obviating the necessity of sampling procedures.

In a regression setting, the training samples comprise  $D = \{x_i, y_i\}_{i=1}^N$ , where the target values  $y_i \in \mathbb{R}$  comprise an i.i.d. Gaussian distribution defined by mean and variance  $\theta = \{\mu, \sigma^2\}$ . Within the context of an evidential depth model, these parameters are presumed unknown and replaced by probabilistic estimates, achieved by placing a Gaussian distribution on the unknown mean  $\mu$  and an Inverse-Gamma prior on the unknown variance  $\sigma^2$ . We obtain a higher-order distribution (also termed the evidential distribution), depicted as  $p(\theta|m)$ , represented by a Normal Inverse-Gamma distribution. This evidential distribution is determined through four parameters,  $m = \{\gamma, v, \alpha, \beta\}$ . The model can capture predictive uncertainty by learning these parameters, as demonstrated in Figure 2. In this work, the uncertainty estimation of the regression model is achieved by setting the chemprop package(2) uncertainty\_method to evidential\_total.



Moreover, to better assist users in assessing the reliability of model predictions based on model uncertainty, furthermore, we furnish the range of model RMSE within different uncertainty intervals. This aids users in assessing the reliability of model predictions based on varying levels of uncertainty.

### Classification model

In the classification model, uncertainty is estimated using the Monte Carlo dropout t approach (5). This method considers dropout in deep neural networks as an approximate Bayesian inference of deep Gaussian processes. Specifically, the dropout technique involves applying dropout before each layer during training and maintaining dropout activation during the inference process. This allows for the generation of prediction distributions using different random masks, approximating the posterior of deep Gaussian processes. The variance of this distribution serves as an estimation of predictive uncertainty (6-8).

During experiments with uncertainty quantification, an ensemble of models generates a prediction distribution for each molecule using a dropout-enabled network with a sample size of 10. The probability of 0.1 to use for Monte Carlo dropout uncertainty estimation. Let  $y_t$  represent the prediction from a single model within the ensemble, which contains  $T = 10$  models. For a query sample  $x_i$ , the prediction  $\hat{y}$  is represented as the means of all predictions and the uncertainty of this sample  $U(x)$  can be provided by the variance  $\sigma_t^2$  of the prediction distribution.

$$U(x) = \sigma^2 = \frac{1}{T-1} \sum_{t=1}^T (y_t - \hat{y})^2 \quad (7)$$

We employed the method proposed by Dolezal et al (9). to determine the optimal uncertainty threshold value,  $\theta$ . This method establishes an uncertainty threshold, where predictions below this threshold are more likely to be correct than those with higher levels of uncertainty. To find the uncertainty threshold that optimally separates predictions into likely-correct (high-confidence) and likely-incorrect (low-confidence), we calculated the sensitivity and specificity for misprediction for all possible uncertainty thresholds. The corresponding Youden's index ( $J$ ) for each uncertainty threshold  $\theta_i$  is the calculated as

$$J_i = Se_i + Sp_i - 1 \quad (8)$$

The optimal uncertainty threshold  $\theta$  is the defined as the threshold which maximized the Youden's index:

$$\theta = \text{argmax} J_i \quad (9)$$

The single threshold is then used for all predicted made by the model. We take a binary a binary approach to confidence using the uncertainty threshold, with confidence of the classification model defined as

$$C(x) = \begin{cases} \text{high - confidence} & \sigma^2(x) < \theta \\ \text{low - confidence} & \sigma^2(x) \geq \theta \end{cases} \quad (10)$$

In other words, prediction uncertainty exceeding this value designates the model's prediction as low confidence, while prediction uncertainty below this threshold indicates high confidence in the model's prediction. This threshold will be used to assess the reliability of prediction in classification tasks within the ADMET models.



BCF	676	540	68	68
IGC50	1787	1429	179	179
LC50FM	816	652	82	82
LC50DM	347	277	35	35
NR-AR	7312 (266/7046)	5848 (212/5636)	732 (27/705)	732 (27/705)
NR-AR-LBD	6862 (233/6629)	5489 (186/5303)	686 (23/663)	687 (24/663)
NR-AhR	6603 (763/5840)	5282 (610/4672)	660 (76/584)	661 (77/584)
NR-Aromatase	5887 (256/5631)	4708 (204/4504)	589 (26/563)	590 (26/564)
NR-ER	6166 (669/5497)	4932 (535/4397)	617 (67/550)	617 (67/550)
NR-ER-LBD	7052 (342/6710)	5641 (273/5368)	705 (34/671)	706 (35/671)
NR-PPAR-gamma	6586 (197/6389)	5268 (157/5111)	659 (20/639)	659 (20/639)
SR-ARE	5652 (865/4787)	4521 (692/3829)	565 (86/479)	566 (87/479)
SR-ATAD5	7170 (249/6921)	5735 (199/5536)	717 (25/692)	718 (25/693)
SR-HSE	6319 (360/5959)	5055 (288/4767)	632 (36/596)	632 (36/596)
SR-MMP	5913 (892/5021)	4729 (713/4016)	591 (89/502)	593 (90/503)
SR-p53	6915 (456/6459)	5531 (364/5167)	692 (46/646)	692 (46/646)

**Supplementary Table 2. Optimal hyperparameters for DMPNN models**

Hyperparameter	Regression					Classification				
	Absorption	Distribution	Excretion	PCP	Toxicity	Absorption	Metabolism	Tox21	Toxicity	
depth	2	5	4	3	4	2	4	4	6	
dropout	0.1	0.1	0.1	0.15	0.05	0.4	0.3	0	0.35	
ffn_hidden_size	1900	1300	1900	2200	1200	1900	1900	1300	2300	
ffn_num_layers	3	3	3	3	3	3	3	3	1	
hidden_size	900	1200	1100	900	1100	1900	900	600	1400	
batch_size	128	128	128	128	128	128	128	128	128	
epochs	200	200	200	200	200	200	200	200	200	

Supplementary Table 3. Optimal hyperparameters for DMPNN-Des models

Hyperparameter	Regression					Classification			
	Absorption	Distribution	Excretion	PCP	Toxicity	Absorption	Metabolism	Tox21	Toxicity
depth	5	5	4	4	4	4	5	6	4
dropout	0.25	0.3	0.3	0.1	0.15	0.05	0.15	0.25	0.3
ffn_hidden_size	800	800	300	2000	300	1400	400	400	1900
ffn_num_layers	1	3	1	3	3	1	3	3	2
hidden_size	2000	2000	1100	1000	2400	1200	600	1200	800
batch_size	128	128	128	128	128	128	128	128	128
epochs	200	200	200	200	200	200	200	200	200



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Validation set	0.751±0.061	0.742±0.083	0.497±0.047	0.748±0.066	0.747±0.089	0.506±0.056	0.692±0.083	0.804±0.120	0.591±0.082
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SR-p53	Test set	0.890±0.027	0.882±0.034	0.415±0.036	0.870±0.027	0.914±0.010	0.445±0.022	0.854±0.016	0.813±0.032	0.339±0.031
	Validation set	0.905±0.021	0.885±0.044	0.489±0.056	0.884±0.012	0.917±0.012	0.486±0.042	0.898±0.049	0.823±0.031	0.392±0.074

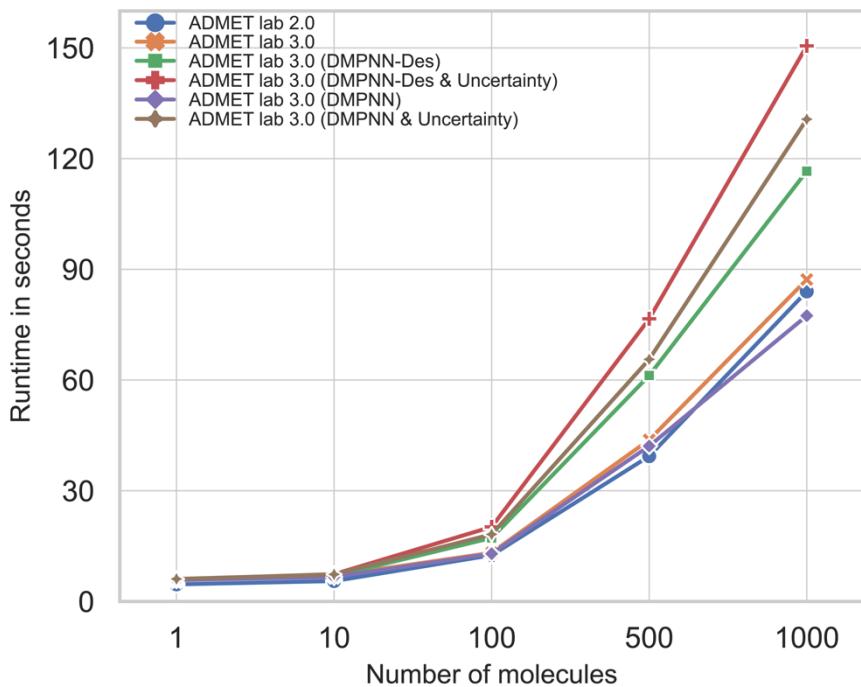


**Supplementary Table 7. The optimal uncertainty thresholds determined by maximum Youden's index for various properties in classification model.**

Dataset	DMPNN-Des		DMPNN	
	Uncertainty threshold	Max Youden's index	Uncertainty threshold	Max Youden's index
PAMPA	0.00116	0.244	0.00023	0.367
Pgp-inhibitor	0.00068	0.418	0.00049	0.518
Pgp-substrate	0.00059	0.343	0.00013	0.555
HIA	0.00050	0.602	0.00001	0.496
F20%	0.00075	0.485	0.00014	0.469
F30%	0.00069	0.412	0.00047	0.466
F50%	0.00150	0.296	0.00025	0.455
CYP1A2 inhibitor	0.00024	0.486	0.00060	0.556
CYP1A2 substrate	0.00091	0.380	0.00010	0.438
CYP2C19 inhibitor	0.00030	0.428	0.00058	0.473
CYP2C19 substrate	0.00089	0.288	0.00040	0.404
CYP2C9 inhibitor	0.00021	0.459	0.00031	0.461
CYP2C9 substrate	0.00567	0.344	0.00024	0.319
CYP2D6 inhibitor	0.00053	0.456	0.00057	0.525
CYP2D6 substrate	0.00263	0.282	0.00023	0.324
CYP3A4 inhibitor	0.00027	0.458	0.00044	0.505
CYP3A4 substrate	0.00033	0.291	0.00030	0.407
CYP2B6 inhibitor	0.00538	0.363	0.00023	0.400
CYP2B6 substrate	0.00018	0.461	0.00057	0.660
CYP2C8 inhibitor	0.00067	0.483	0.00031	0.552
HLM Stability	0.00176	0.403	0.00045	0.335
hERG Blockers	0.00027	0.521	0.00007	0.543
hERG Blocker (10um)	0.00156	0.517	0.00042	0.600
DILI	0.00008	0.669	0.00008	0.674
AMES Mutagenicity	0.00047	0.646	0.00011	0.640
ROA	0.00196	0.409	0.00024	0.316
FDAMDD	0.00025	0.662	0.00041	0.642
Skin Sensitization	0.00046	0.693	0.00019	0.712
Carcinogenicity	0.00063	0.367	0.00011	0.344
Eye Corrosion	0.00029	0.729	0.00019	0.696
Eye Irritation	0.00062	0.549	0.00011	0.575
Respiratory	0.00017	0.559	0.00005	0.470
Human Hepatotoxicity	0.00024	0.608	0.00006	0.612
Drug-induced Neurotoxicity	0.00029	0.460	0.00028	0.484
Ototoxicity	0.00104	0.322	0.00050	0.293
Hematotoxicity	0.00185	0.478	0.00049	0.430
Drug-induced Nephrotoxicity	0.00075	0.375	0.00036	0.366
Genotoxicity	0.00147	0.369	0.00033	0.338
RPMI-8226 Immunitoxicity	0.00044	0.327	0.00039	0.286
A549 Cytotoxicity	0.00359	0.328	0.00020	0.370
Hek293 Cytotoxicity	0.00080	0.206	0.00033	0.194
NR-AhR	0.00007	0.656	0.00016	0.691
NR-AR	0.00003	0.590	0.00029	0.653
NR-AR-LBD	0.00268	0.337	0.00031	0.396
NR-Aromatase	0.00255	0.262	0.00046	0.242
NR-ER	0.00402	0.288	0.00088	0.351
NR-ER-LBD	0.00200	0.300	0.00037	0.227
NR-PPAR-gamma	0.00115	0.376	0.00044	0.351
SR-ARE	0.00074	0.263	0.00034	0.225
SR-ATAD5	0.00005	0.538	0.00046	0.633
SR-HSE	0.00043	0.567	0.00056	0.589
SR-MMP	0.00080	0.542	0.00056	0.607
SR-p53	0.00135	0.417	0.00045	0.443

**Supplementary Table 8.** Runtime analysis in seconds for submissions of 1 to 1000 molecules for ADMETlab 2.0 and ADMETlab 3.0 with different modelling options.

Number of molecules	ADMETlab2 .0	ADMETlab3 .0 (web portal)	ADMETlab3. 0 (DMPNN-Des)	ADMETlab3. .0 (DMPNN-Des & Uncertainty)	ADMETlab3 .0 (DMPNN)	ADMETlab3 .0 (DMPNN & Uncertainty)
1	4.63	5.75	5.80	6.03	5.79	6.09
10	5.52	6.97	6.89	7.39	6.63	7.34
100	12.52	13.19	17.21	20.20	12.93	18.18
500	39.36	43.78	61.23	76.58	42.10	65.60
1000	84.00	87.23	116.59	150.54	77.42	130.66



Supplementary Figure 1. Runtime analysis in seconds for submissions of 1 to 1000 molecules for ADMETlab 2.0, ADMETlab 3.0 (DMPNN-Des), ADMETlab 3.0 (DMPNN-Des & Uncertainty), ADMETlab 3.0 (DMPNN), and ADMETlab 3.0 (DMPN & Uncertainty).

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