

#### Project Report

### **Cytotoxicity of Nanoparticles**

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### Introduction

 Cytotoxicity of Nanoparticles refers to the capacity of materials between 1 and 100 nanometers in size to cause cellular damage or death due to their interaction with biological entities at a molecular level.

#### Tasks:

- Regression: predicting continuous values representing cell viability.
- Classification: categorizing cell viability as either high (viability ≥ 85%) or low.

#### Outcomes:

- 1. Optimized data pipelines and hyperparameters for TabPFN-v2.
- 2. Analysis on the optimization process.

### **Data - Properties**

**Table 1. Visualization of Target variable of Regression Task** 

	Train	ning set	Test set			
	Regression	Classification	Regression	Classification		
Features	20					
Examples	1775		762			
Missing-value examples	1102		475			
High-viability examples	- 910		-			
Low-viability examples	- 865		-			

### **Data - Properties**

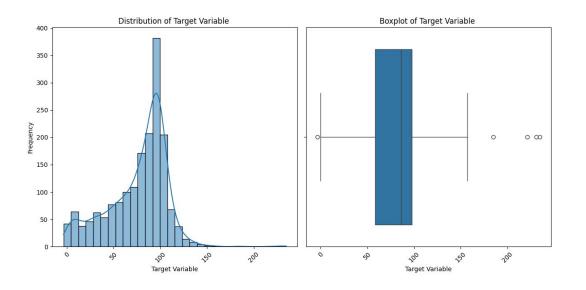


Fig 1. Visualization of Target variable of Regression Task

### **Data - Processing**

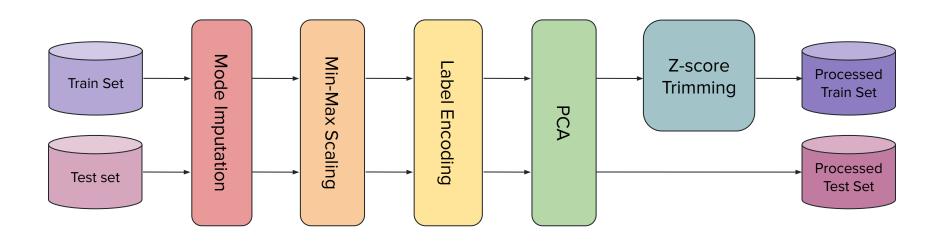


Fig 2. Optimized Data Pipeline for Regression Task

### **Data - Processing**

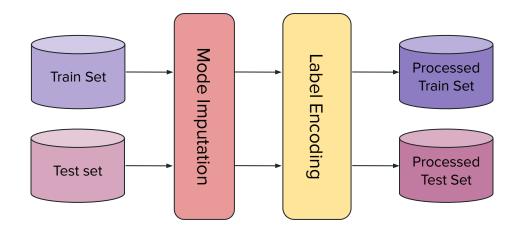


Fig 3. Optimized Data Pipeline for Classification Task

### **Architecture**

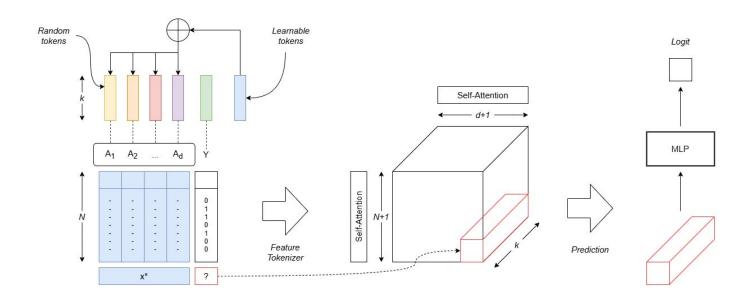


Fig 4. Architecture of TabPFN-v2 Regressor

### **Architecture**

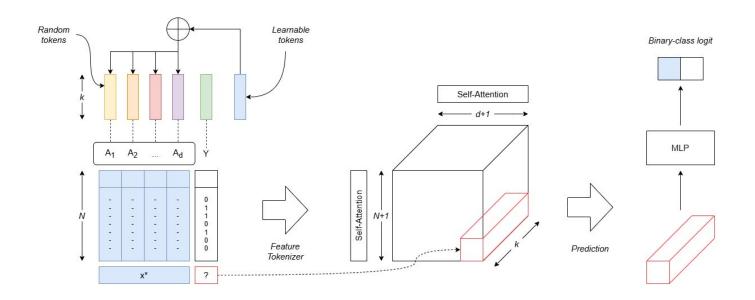


Fig 5. Architecture of TabPFN-v2 Classifier

### **Implementation Details**

- All experiments were conducted on a P100
  16GB GPU hosted on Kaggle and a local
  NVIDIA GTX1650Ti 4GB GPU
- The random seed consistently set to 42 to ensure reproducibility.
- The models included in the comparative analysis can be broadly categorized into two types: data-driven and knowledge-driven.
- Baseline models and ablation studies used default hyperparameters and a simple data pipeline with only a label encoding step, while the optimized ones utilized the optimized hyperparameters and data pipelines.

Table 2. Optimized Hyperparameters for TabPFN-v2

Hyperparameter	Regressor	Classifier	
Number of estimators	10	10	
Softmax temperature	0.5	0.5	
Average before softmax	True	True	

Table 3. Training hyperparameters for LLMs

Hyperparameter	GPT2	BioGPT
Training batch size	72	45
Number of epochs		40
Warm-up ratio (%)	10	
Learning rate	1e-4	
Weight decay	1	
BF-16	7	True

### **Implementation Details**

Table 4. Examples of Input Text for LLMs

#### Training

Predict the viability of a cell. The material of the nanoparticle is Pt. The nanoparticle is inorganic. The morphology of the nanoparticle is Sphere. The fabrication method is Chemical Reduction. The surface coating is PVP. The cell type is IMR90. The number of cells (cells/well) is 5000.0. The origin species of the cell is human. The source of the cell line is Human. The type of cell tissue is Lung. The morphology of the cell is Fibroblast. The cell is in Adult stage. The cell is cell line. The exposure time is 24 hours. The exposure concentration is 25.0 ug/ml. The type of cytotoxicity test is CellTiterGlo. The test mechanism is LuciferaseEnzyme. The size of the nanoparticle is 4.0 nm. The zeta potential indicating surface charge stability of the nanoparticle is -8.0 mV. The surface charge is Negative. Viability (%): 98.293

#### Inference

Predict the viability of a cell. The material of the nanoparticle is Ag. The nanoparticle is inorganic. The morphology of the nanoparticle is Sphere. The fabrication method is Commercial. The surface coating is Citrate. The cell type is CCL-110. The number of cells (cells/well) is 5000.0. The origin species of the cell is human. The source of the cell line is Human. The type of cell tissue is Skin. The morphology of the cell is Fibroblast. The cell is in Fetus stage. The cell is primary. The exposure time is 24 hours. The exposure concentration is 0.5 ug/ml. The type of cytotoxicity test is MTS. The test mechanism is TetrazoliumSalt. The size of the nanoparticle is 39.94 nm. The zeta potential indicating surface charge stability of the nanoparticle is -23.5 mV. The surface charge is Negative. Viability (%):

### **Main Results**

**Table 5. Main Results** 

Drive	Method	thod Data (%)		Cross-validation		Regression test set		Classification test set	
Drive	Wiethou	Data (%)	Avg. R2	Avg. MCC	$R^2$	Inference time (s)	MCC	Inference time (s)	
	Logistic Regression	100	100 To 100	0.2750	1 <del>.</del>	-	0.16989	0.0041	
	Linear Regression	100	0.1816	-	0.16989	0.0048	- 1	-	
Data Random Gradient	Decision Tree	100	0.6677	0.6460	0.76673	0.0008	0.71634	0.0012	
	Random Forests	100	0.8044	0.6966	0.84581	0.0086	0.76629	0.0062	
	Gradient Boosting	100	0.6607	0.6656	0.65157	0.0026	0.69814	0.0017	
	TabPFN-v2	90	0.8051	0.7245	0.85896	0.6432	0.76895	0.3127	
	TabPFN-v2	100	0.8122	0.7237	0.86839	0.6862	0.76104	0.3397	
	TabPFN-v2 (Optimized)	100	0.8480	0.7300	0.88296	0.8713	0.79255	0.8338	
	GPT2	100	-	-	0.78022	2.4049	-	1111	
Knowledge	BioGPT	100	-	. 3	0.79314	4.1377		-	

## **Ablation Studies - Missing Values**

**Table 6. Results of Missing Values Handling** 

Method	Cross-	validation	Test set		
Method	Avg. $R^2$	Avg. MCC	$R^2$	MCC	
None	0.8122	0.7237	0.86839	0.76104	
Mode	0.8200	0.7173	0.87879	0.78216	

### **Ablation Studies - Feature Scaling**

**Table 7. Results of Feature Scaling** 

Method	Cross-	validation	Test set		
	Avg. $R^2$	Avg. MCC	$R^2$	MCC	
None	0.8122	0.7237	0.86839	0.76104	
Standard	0.8115	0.7216	0.86839	0.76625	
Min-Max	0.8131	0.7186	0.86908	0.76629	

### **Ablation Studies - Feature Encoding**

**Table 8. Results of Feature Encoding** 

Method	Cross-	validation	Test set		
Method	Avg. $R^2$	Avg. MCC	$R^2$	MCC	
Label	0.8122	0.7237	0.86839	0.76104	
One-hot	0.8096	0.7007	0.86474	0.77946	
Target	0.7869	0.6960	0.85966	0.76125	

### **Ablation Studies - Dimensionality Reduction**

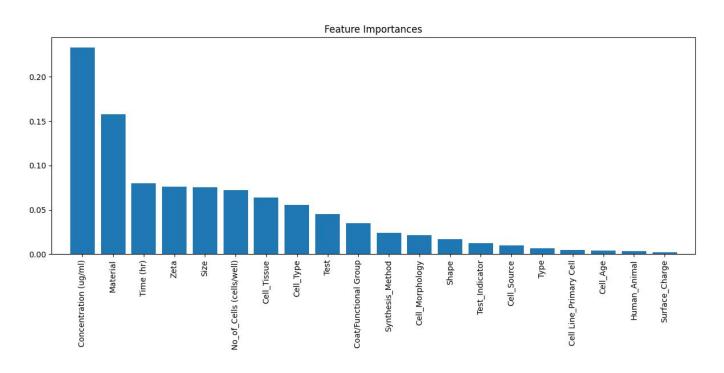


Fig 6. Feature importance in Regression Task

### **Ablation Studies - Dimensionality Reduction**

**Table 9. Results of Dimensionality Reduction** 

Reduced features					Cross-validation		Test set	
Surface_charge	Human_Animal	Cell_Age	Cell Line_Primary Cell	Avg. R2	Avg. MCC	$R^2$	MCC	
				0.8122	0.7237	0.86839	0.76104	
<b>√</b>				0.8130	-	0.86905	1724	
	<b>√</b>		<u> </u>	0.8107	-	0.87177	150	
		<b>√</b>		0.8072	12.1	0.86846	17.0	
			<b>√</b>	0.8099	-	0.87034	178	
<b>√</b>	<b>√</b>			0.8163	-	0.86997	:=:	
<b>√</b>	<b>√</b>	<b>√</b>		0.8172	3 <b>#</b> 3	0.87186	1,70	
<b>√</b>	<b>√</b>	1	<b>√</b>	0.8177	-	0.87095	-	

### **Ablation Studies - Outliers**

**Table 10. Results of Outliers Handling in Regression Task** 

Detection	Handling		Cross-validation		Test set	
Detection	Trim	Clip	Avg. $R^2$	Avg. MCC	$R^2$	MCC
None			0.8122	0.7237	0.86839	0.76104
IOD	<b>√</b>		0.8408	-	0.86913	-
IQR		<b>✓</b>	0.8288	2	0.86816	-
7	<b>√</b>		0.8418	-	0.86737	-
Z-score		<b>√</b>	0.8291	-	0.86928	-

### Conclusion

#### • Findings:

- The experiments demonstrated the effectiveness of the TabPFN-v2 architecture, especially when combined with an optimized data pipeline.
- The optimized model outperforming other evaluated methods in both regression (R-squared:
  0.88296) and classification (MCC: 0.79255) tasks on the test set.
- **Limitations:** The inference time of TabPFN-v2 was substantially longer compared to traditional machine learning models and appeared to increase with the size of the training data.

#### Future Directions:

- Future research could focus on reducing the inference time of the TabPFN-v2 model.
- Exploring the applicability of TabPFN-v2 to larger, high-dimensional datasets is another potential area for future investigation.



**Q&A** 

<sup>\*</sup> Code and materials can be found at: <a href="https://github.com/tanthinhdt/cbbl-2025">https://github.com/tanthinhdt/cbbl-2025</a>