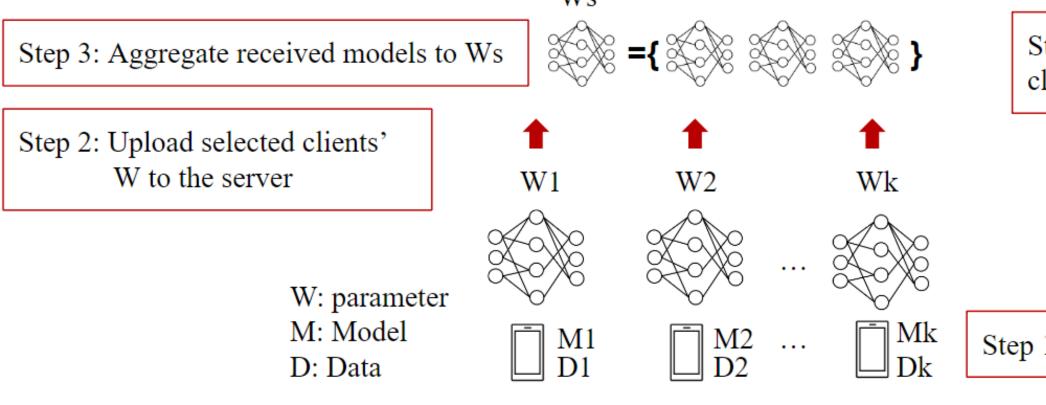




## Background and Motivati

> Federated learning (FL) enables multiple models collaboratively without sharing le has achieved promising results in different the Internet of Things (IoT).



### > Motivation

- In the real world scenario, it is impractication local data is fully labelled, since users us any incentives or have the expertise generated data.
- > A general global model may not characterize the uniqueness of each lo devices may store heterogeneous dat customization has become a rigid applications.
- Existing methods are not developed for and do not take into account the constrai such as limited computational resources network bandwidth.

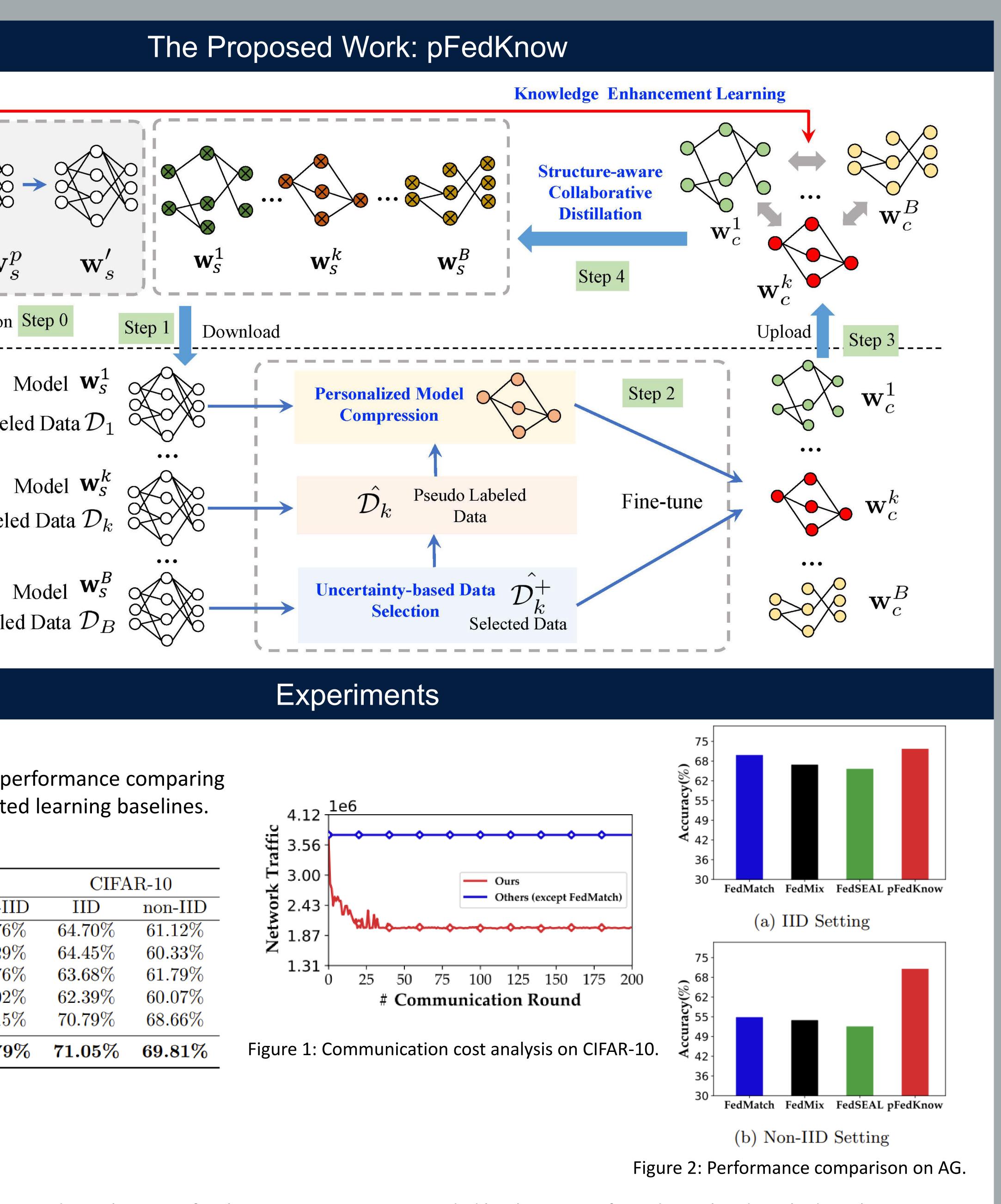
#### Contribution

- > To the best of our knowledge, we are distill lightweight models to warm customize compressed local models structures using network pruning techniq
- > We propose a new aggregation app combination of network structure-awa distillation and large-model knowledge learning.

# **Knowledge-Enhanced Semi-Supervised Federated Learning for Aggregating Heterogeneous Lightweight Clients in IoT**

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on			
e clients to train ocal data, which areas, including	Server Update Labeled Dat $\mathcal{D}_s$		
	Global	Model Initi	alization
1: train local models with local data			Unlabel
al to assume that sually do not take to annotate the	Local Update		Jnlabele
be sufficient to oT user since IoT ta. Thus, model need for IoT		Ū	Jnlabele
r IoT applications ints of IoT devices and constrained	Table 1: Image classification pe with semi-supervised federate		
the first work to up and further with <b>different</b> ques in FL. <b>broach</b> with the <b>are collaborative</b> <b>ge enhancement</b>	Dataset Setting FedMatch [8] SSFL [39] FedMix [38] FedSEAL [1] SemiFL [4] pFedKnow	SV IID 78.34% 76.06% 78.45% 72.64% 84.65% 85.31%	HN non-II 74.76 70.29 71.76 69.02 82.15 84.79
	Acknowledg	ement. ro	gistratic



ed learning baselines.

	CIFAR-10			
D	IID	non-IID		
76	64.70%	61.12%		
76	64.45%	60.33%		
76	63.68%	61.79%		
76	62.39%	60.07%		
76	70.79%	68.66%		
%	$\mathbf{71.05\%}$	69.81%		

