Federated Neural Network Based Refurbished Mobile Phone Pricing Framework for E-Commerce Platforms

Abstract

The growing market for used cell phones has necessitated the development of realistic pricing models that can operate while maintaining data privacy. The paper presents a federated learning framework designed to predict the prices of refurbished mobile phones while ensuring data privacy. It addresses the challenges of traditional centralized data approaches by allowing multiple retail stores to train machine learning models on their local data without sharing sensitive information. The architecture includes various seller clients, such as flagship and mid-range stores, contributing diverse data for improved model accuracy. The framework utilizes a FedAvg strategy to aggregate model updates, enhancing the central model's performance without compromising individual data security. The findings demonstrate that federated learning can effectively balance privacy and prediction accuracy, offering a robust solution for e-commerce platforms. This research contributes to the growing need for secure and effective pricing strategies in the used mobile phone market.

CCS Concepts

• **Computing methodologies** → **Artificial intelligence**; **Distributed artificial intelligence**; **Mobile agents**;

Keywords

Federated Learning, Phone Price Prediction, Flower Framework, Deep Learning

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1 Introduction

The global demand for second-hand smartphones is increasing due to the adaptability of people to new technology and trends. Used cell phones are typically cheaper than new ones, making them accessible to a wider range of individuals, especially those on a tight budget. They often offer comparable performance to new mid-range or affordable devices. Online platforms maintain their prominence in the used smartphone industry due to easy communication between buyers and sellers [2]. Factors such as battery life, colour, RAM, and wifi capabilities influence consumer preference for high-quality devices [9]. To make a purchase, it is crucial to develop a price estimate considering various factors, dividing phone price ranges into cheap, medium, high, and extremely expensive [5]. Social media is a major platform for buying and selling used smartphones, with thousands of users exchanging their devices daily. However, the main challenge is satisfaction, as many buyers are disappointed with the value for money or the price. Sellers can be untrustworthy, selling stolen devices or falsifying information. Identifying authentic second-hand smartphones is challenging, and negotiating a reasonable price can be challenging, especially for buyers unfamiliar with the market. Factors affecting price include brand, model, condition, and changing consumer demand.

Traditional price prediction algorithms use centralized machine learning techniques, but they face challenges in data security, scalability, and equity. Accessing large amounts of user data can expose private information, especially in marketplaces handling consumer data and user-owned devices [12]. Federated learning (FL) is proposed to address these issues, protecting data privacy, boosting productivity, and allowing customization in machine learning model training. This approach could significantly change the development and execution of AI applications across various fields [11]. Federated learning is a method where decentralized organizations train a shared model without sharing data directly. Each individual uses their data to train the model, providing updates to a central server. This approach maintains prediction accuracy and privacy by avoiding sensitive data leaving the local region [23]. Federated learning leverages the combined processing capacity of multiple devices, allowing it to handle big datasets and train models at the network's edge, reducing latency and providing real-time insights [18].

Decentralized federated learning (DFL) is a method that ensures data privacy and increases system resilience by preventing the centralization of data and computations. It is useful for training machine learning models when data privacy is a concern and scattered computing resources are available [8]. DFL uses local data from participating organizations to train a machine learning model, resulting in more accurate predictions for used phone pricing. This decentralized approach maintains individual consumer privacy while utilizing market collective wisdom, promoting cooperation between entities [21]. With all these in mind, we designed our own e-commerce-centric federated price training. Our key contributions are:

- We propose a federated learning for a refurbished mobile phone price prediction engine.
- We ensure customer data protection and privacy by simulating the federated training between several real-life shops as clients and an e-commerce platform as the server. This solves the issue of maintaining and migrating databases regularly. Sensitive customer data never leaves the local shops.
- We show that federated learning can be utilized without compensating performance. This ensures applications can

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balance performance cost to privacy ratio by shifting to federated training.

2 Related Works

Predicting used mobile phone prices is crucial due to the growing market and machine learning potential. Machine learning and deep learning have improved accuracy and flexibility in this dynamic market by modelling nonlinear correlations between variables like brand popularity, age, phone condition, and regional demand.

Machine learning (ML) algorithms analyze structured data like device brand, age, and condition for early price prediction. However, linear regression often fails to capture complex, non-linear correlations. Bakir et al. compare Support Vectors and Long Short-Term Memory (LSTM) models for European phone prices, showing that LSTM outperforms SVR [6]. Asim et al. predict mobile phone price classes using classifiers like Decision Tree and Naive Bayes, with WrapperattributEval achieving 78% accuracy [3]. While this work optimizes product selection with minimal features, it has low accuracy due to a limited dataset and feature set. Chen et al. improved the Multilayer Perceptron classifier's performance in mobile phone price prediction by comparing feature reduction techniques like Pearson's correlation and PCA [9]. The model achieved 95.85% accuracy using correlation-based feature selection, while PCA underperformed, especially when using only top 5 features. Jose et al. tested seven models, with Support Vector Machine (SVM) achieving the highest accuracy of 97.9% [13]. Advanced techniques like random forests and gradient boosting machines enhance accuracy and resilience.

Atzmon et al. estimated mobile phone sales using a mix of temporal and structural data [4]. They used a dense neural network for static characteristics and LSTM networks for temporal correlations. Their model outperformed conventional statistical models by 18% on a dataset of over 50,000 sales records. Kumar et al. used deep neural networks to anticipate smartphone pricing in 2020, utilizing a dataset of smartphone characteristics, market trends, and past prices [15]. Their method outperformed conventional machine learning. DL models, however, come with their own set of difficulties. According to Xu et al. (2021), inconsistent data, including incorrectly labelled conditions, can have a substantial impact on the performance of the DL model and result in fewer accurate predictions [24]. As a result, even while deep learning algorithms have sophisticated prediction skills, they encounter difficulties with high processing requirements and model interpretability.

Federated Learning (FL) is a revolutionary approach to machine learning that addresses data privacy and computational efficiency issues. It allows for collaborative model training across multiple devices without requiring centralized data aggregation, making it particularly useful in sensitive data-intensive situations like the used phone market. Kairouz et al. (2021) further highlighted FL's flexibility and scalability, demonstrating its ability to adapt dynamically to diverse data distributions and device properties [14]. This is particularly useful in the secondhand phone market, where data quality and relevancy vary significantly. Liu and Brown (2021) presented a method for mobile phone price prediction that combines federated learning and edge computing, predicting pricing based on smartphone characteristics and user-generated data [17]. The system processes data locally, reducing reliance on centralized servers.

Prior studies demonstrate that FL can be adjusted to attain performance levels comparable to centralized models and can be more economically viable by using local devices for processing [10]. Nonetheless, there are still issues, especially with managing heterogeneous data and maintaining security. Model performance may be impacted by differences in data distributions between areas, but this risk may be lessened with the use of strategies such as local fine-tuning [16]. Furthermore, privacy attacks may target FL systems, therefore additional security measures like safe aggregation and differential privacy must be used [22].

3 Methodology

This section discusses the proposed methodology of the research work. The system architecture, data preparation, and federated clients are covered here. All the experiments here were done on a machine equipped with NVIDIA RTX 3060 GPU and AMD RYZEN 7 5700X CPU equipped laptop. TensorFlow was used as the deep learning back-end [1].

3.1 Dataset

Figure 1 shows the dataset preparation stage for the federated learning approach. The original dataset is collected from Kaggle [20]. This contains 15 features and 3454 rows. The dataset was first checked for rows with missing values and those rows were dropped. The categorical features were label-encoded. The data is then divided into clusters using the k-means algorithm. The cluster with a higher average price was categorized as the flagship and the other as mid-range devices. The clusters were saved as the database of different stores.

3.2 System Architecture

We created this framework based on the concept of an e-commerce website that sells refurbished and used mobile phones or cellular devices. It has many seller clients who sell devices of different price categories. Flagship stores sell mostly pricey and premium devices (priced over 700$). On the contrary, mid-range device-centric stores mostly have cheaper devices to offer. We aim to train neural network models on the local data of each store while maintaining customer privacy. The trained weights of the client models are then sent to the website model. Without sending any data from the local stores the website model is automatically updated with the trained weights ensuring transparency and information security.

Our approach is based on the flower federated learning library [7]. We have taken two clients for this work, but Flower is scalable and can be used with n number of clients. Figure 2 depicts the architecture of this project. The two clients are flagship and mid-range, representing the two local shops. They have their respective databases of customers and sold device information. A neural network model is trained on the local data and the weights are sent to the website server. A FedAvg strategy aggregates those weights and the website server model is equipped with the aggregated weight.

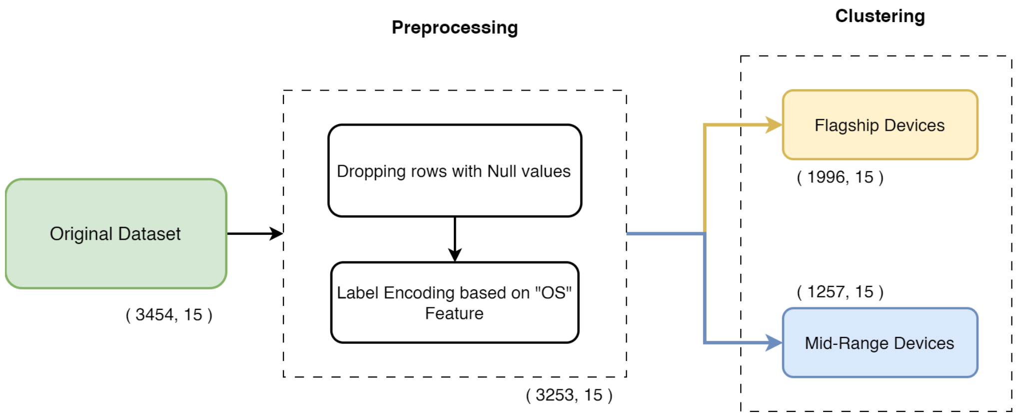

Figure 1: Federated dataset preparation for different clients

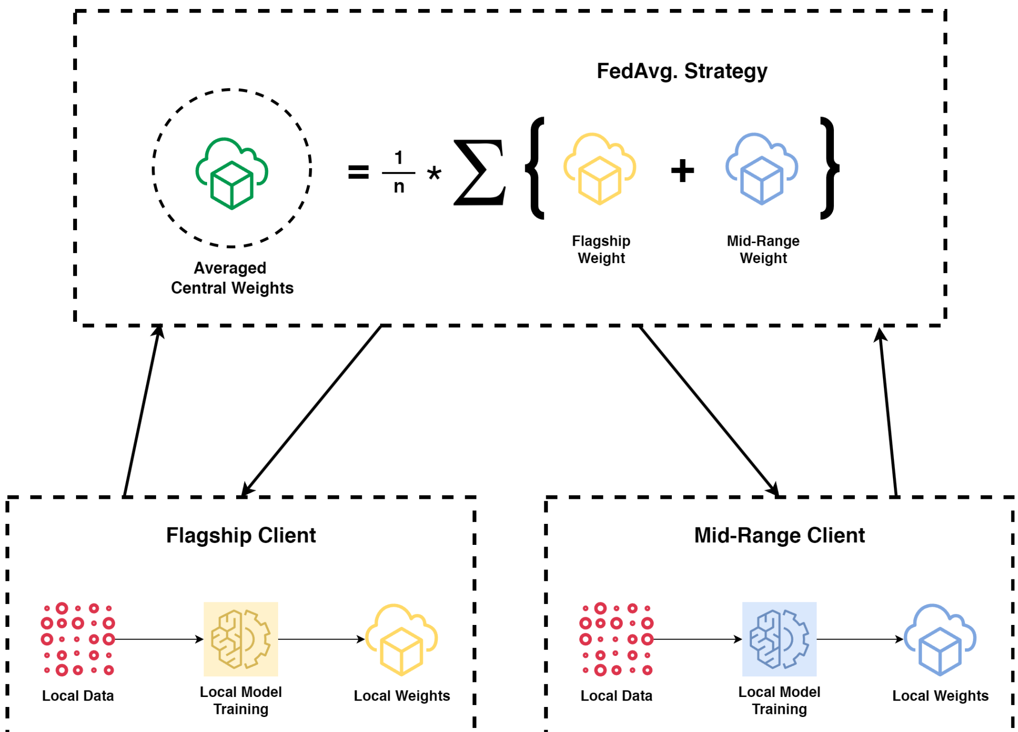

Figure 2: Federated Flower framework

3.3 Metrics

As the problem is a regression analysis, to analyze the model learning and evaluation Mean absolute error (MAE), Mean absolute percentage error (MAPE) and Root mean squared error (RMSE) were selected.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

These metrics determine the deviation between actual and predicted values. Lower values of MAPE, MAE and RMSE suggest that the model can predict closely to the actual values.

3.4 Centralized Training

A simple neural network model was built for this experiment. The model summary is shown in table 1. The central training is the typical model training where all the data and models are stored centrally. The model was trained on the total dataset before clustering. For 100 epochs, the model was trained with a batch size of 32. By doing this we created baseline metrics and moved forward to federated learning.

Table 1: Neural network model summary

Layer	Activation	**Output Shape**	**Param #**
dense	ReLU	(None, 32)	480
dense_1	ReLU	(None, 16)	528
dense_2	-	(None, 1)	17
Total params:			**1,025**
Trainable params:			**1,025**
Non-trainable params:			**0**

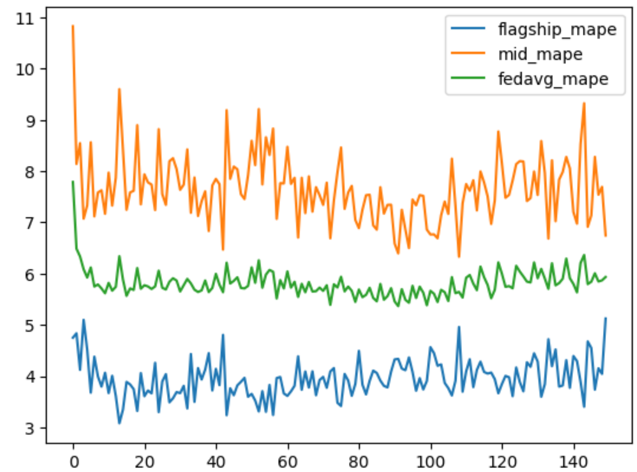

Figure 3: MAPE comparison between clients and FedAvg model

3.5 Federated Training

As stated, two clients were created for this task. The same neural network stated in table 1 was used for both the clients. This time the epoch was set to 10 and batch size was kept the same as the central model. MAPE was assigned as the loss function. To compile the model Adam optimizer was used with the learning rate set to 3e-4. The flagship client only received the flagship data and the mid-range client gets only the mid-range data.

The server is started first, and separate client scripts are then run. The models start training with the mentioned attributes. The server model is trained for 150 communication rounds. This means the client weights are sent to the server 150 times. In the server, the federated average or FedAvg strategy was used to aggregate the weights [19]. For 2 clients, the global model update is written as:

$$\mathbf{w}_{t+1} = \frac{n_1}{n_1 + n_2}\mathbf{w_{flag}}^{t+1} + \frac{n_2}{n_1 + n_2}\mathbf{w_{mid}}^{t+1} \tag{4}$$

where:

- $\mathbf{w}_{t+1}$ is the server model weight after aggregation at round $t + 1$,
- $\mathbf{w_{flag}}^{t+1}$ and $\mathbf{w_{mid}}^{t+1}$ are the local model weights from flagship and mid-range clients, respectively,
- n_1 and n_2 are the data points held by flagship and mid-range clients, respectively.

As the training moves forward, the FedAvg weights are saved in each round. The MAPE loss is monitored throughout the training process.

4 Result Analysis

This table 2 compares the performance of two models, Central and FedAvg, across three datasets: Total, Flagship, and Mid-Range, using three metrics—MAE, MAPE, and RMSE. Overall, the Central model consistently outperforms the FedAvg model in all datasets. For example, in the Total Dataset, the Central model has an MAE of 17.45 and an RMSE of 22.17, whereas the FedAvg model exhibits significantly higher errors, with an MAE of 39.66 and an RMSE of 52. Similarly, the Central model achieves a lower MAPE of 0.04 compared to 0.09 for the FedAvg model, indicating a better fit. The pattern holds across the Flagship and Mid-Range datasets as well. In the Flagship Dataset, the Central model's MAE (17.08) and RMSE (20.88) are notably lower than those of the FedAvg model (MAE: 40.89, RMSE: 52.81). A similar trend is seen in the Mid-Range Dataset, where the Central model has the lowest error rates, though its performance degrades slightly compared to the other datasets. The FedAvg model, on the other hand, consistently underperforms, with its highest MAPE (0.11) in the Mid-Range Dataset, signalling poorer generalization and higher prediction errors overall.

Figure 3 shows the Mean Absolute Percentage Error (MAPE) for flagship and mid-range customers compared to the FedAvg model. Lower MAPE implies higher prediction accuracy. The chart reveals that the flagship client has a lower MAPE (between 3-5%) than the mid-range client, indicating that the model works better with data from flagship smartphones. The mid-range client exhibited a greater MAPE, possibly due to a smaller sample count. The FedAvg MAPE was in the centre, as predicted, with a consistent 6% loss. Its MAPE is greater than that of the flagship client, implying that, while federated learning improves privacy and data security, it does not attain the same degree of accuracy as a centralized model.

Figure 4 and 5 compare the trained federated model performance with the centrally trained model. Randomly taking 25 samples, we see that the central model is quite close to the original, sometimes overlapping the values. However, the red points representing federated prediction aren't very far off. One thing is obvious, the federated weighted model tends to generalize the predicted prices. As used device prices are always fluctuating, this approach might be more suitable than a strict pattern following a centrally trained model. The Federated model falls behind in predicting drastically changed high or low prices.

Table 2: Metrics comparison between different models and datasets

Model	Total Dataset			Flagship Dataset			Mid-Range Dataset		
	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE
Central	17.45	0.04	22.17	17.08	0.04	20.88	19.4	0.06	25.83
FedAvg	39.66	0.09	52	40.89	0.08	52.81	37.71	0.11	50.69

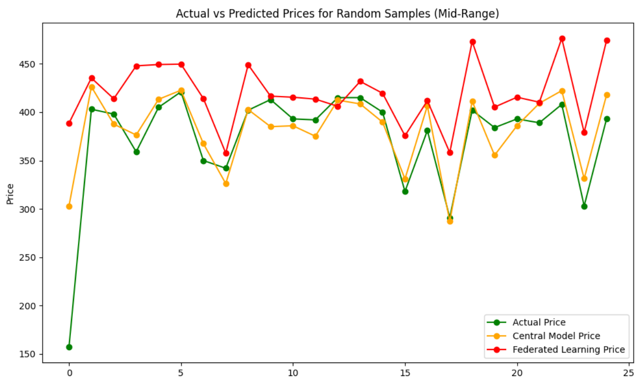

Figure 4: Comparing prediction of mid-range device price

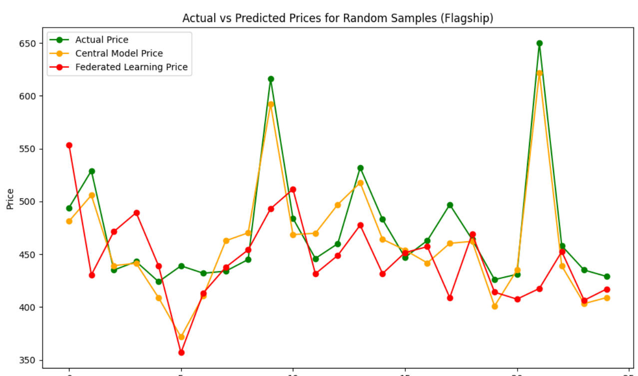

Figure 5: Comparing prediction of flagship device price

5 Discussion

Our study effectively illustrates the efficiency of federated learning for predicting used mobile phone prices. This technique protects user privacy and data security at all stages of training and evaluation. We also discovered that the data imbalance impact was reduced in federated learning. However, we discovered several limits.

- Increasing the communication rounds didn't improve the federated model performance. This might be due to the simplistic neural network used here. On the other hand, client models need to be simple to be trained on less computational power.
- The data disparity showed visible marks in predictions. The federated model performed better on the flagship dataset, as it had better-trained weights than the mid-range client.
- The Federated model takes a generalized approach while predicting, this might be an issue for costlier devices in respective categories
- The dataset didn't account for the condition of the devices. This can act as a huge factor in used device price. A robust dataset collection can justify our findings more.

6 Conclusion

We effectively show the efficacy of federated learning in forecasting used mobile phone costs while respecting user privacy and data security throughout the training and assessment procedures. The findings show that federated learning can reduce the consequences of data imbalance, a typical problem in machine learning applications. However, the study does identify many shortcomings, including a performance gap between the Central and FedAvg models, notably in terms of forecast accuracy. The findings imply that, while federated models can generalize well, they may fail to estimate pricing for devices that have experienced considerable market value fluctuations. Future studies should focus on improving the dataset's resilience and investigating more complicated model architectures to increase forecast accuracy across several devices. Overall, this research contributes to the growing body of knowledge on federated learning and its applications in real-world scenarios, particularly in the mobile phone industry.

References

[1] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dandelion Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. 2015. TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems. https://www.tensorflow.org/ Software available from tensorflow.org.

[2] Seda İpek AKSOY ERCAN and Murat ŞİMŞEK. 2023. Mobile Phone Price Classification Using Machine Learning. *International Journal of Advanced Natural Sciences and Engineering Researches* 7, 4 (May 2023), 458–462. https://doi.org/10.59287/ijanser.791

[3] Muhammad Asim and Zafar Khan. 2018. Mobile price class prediction using machine learning techniques. *International Journal of Computer Applications* 179, 29 (2018), 6–11.

[4] Yuval Atzmon, Amir Rosenfeld, and Shie Mannor. 2019. Predicting Mobile Phone Sales with Deep Learning. In *Proceedings of the International Conference on Predictive Analytics and Data Mining*.

[5] Serpil AYDIN. 2022. USING MACHINE LEARNING ALGORITHMS IN THE CLASSIFICATION OF PRICES ON MOBILE PHONES. *International Research in Science and Mathematics* (2022), 201.

[6] Houda Bakir, Ghassen Chniti, and Hédi Zaher. 2018. E-Commerce price forecasting using LSTM neural networks. *International Journal of Machine Learning and Computing* 8, 2 (2018), 169–174.

[7] Daniel J Beutel, Taner Topal, Akhil Mathur, Xinchi Qiu, Javier Fernandez-Marques, Yan Gao, Lorenzo Sani, Kwing Hei Li, Titouan Parcollet, Pedro Porto Buarque de

Gusmão, et al. 2020. Flower: A friendly federated learning research framework. *arXiv preprint arXiv:2007.14390* (2020).
[8] Di Cao, Shan Chang, Zhijian Lin, Guohua Liu, and Donghong Sun. 2019. Understanding distributed poisoning attack in federated learning. In *2019 IEEE 25th international conference on parallel and distributed systems (ICPADS)*. IEEE, 233–239.
[9] Menghan Chen. 2023. Mobile Phone Price Prediction with Feature Reduction. *Highlights in Science, Engineering and Technology* 34 (2023), 155–162.
[10] Robin C Geyer, Tassilo Klein, and Moin Nabi. 2017. Federated learning with differential privacy: Algorithms and performance analysis. In *Proceedings of the 14th International Conference on Privacy, Security, and Trust (PST)*.
[11] Meng Hao, Hongwei Li, Guowen Xu, Hanxiao Chen, and Tianwei Zhang. 2021. Efficient, private and robust federated learning. In *Proceedings of the 37th Annual Computer Security Applications Conference*. 45–60.
[12] Andrew Hard, Kanishka Rao, Rajiv Mathews, Swaroop Ramaswamy, Françoise Beaufays, Sean Augenstein, Hubert Eichner, Chloé Kiddon, and Daniel Ramage. 2018. Federated learning for mobile keyboard prediction. *arXiv preprint arXiv:1811.03604* (2018).
[13] Jinsi Jose, Vinesh Raj, Sweana Vakkayil Seaban, and Deepa V Jose. 2023. Machine Learning Algorithms for Prediction of Mobile Phone Prices. In *International Conference On Innovative Computing And Communication*. Springer, 81–89.
[14] Patrick Kairouz et al. 2021. Advances and Open Problems in Federated Learning. In *Foundations and Trends in Machine Learning*.
[15] Rohit Kumar, Anjali Sharma, Sandeep Gupta, and Praveen Singh. 2020. Price Prediction Using Deep Neural Networks: A Case Study of Smartphones. In *Proceedings of the International Conference on Machine Learning Applications*.
[16] Tian Li, Arjun Sahu, Ameet Talwalkar, and Virginia Smith. 2020. Heterogeneity in federated learning: A survey and benchmark. *Proceedings of the 3rd Symposium on Advances in Approximate Data Structures* (2020).
[17] Richard Liu and Stephanie Brown. 2021. Federated Learning for Mobile Device Price Estimation: An Edge Computing Approach. In *Proceedings of the International Conference on Edge Computing and Distributed Systems*.
[18] Priyanka Mary Mammen. 2021. Federated learning: Opportunities and challenges. *arXiv preprint arXiv:2101.05428* (2021).
[19] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. 2017. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics*. PMLR, 1273–1282.
[20] Ahsan Raza. 2023. Used Phones & Tablets Pricing Dataset. https://www.kaggle.com/datasets/ahsan81/used-handheld-device-data
[21] Yuris Mulya Saputra, Dinh Thai Hoang, Diep N Nguyen, Eryk Dutkiewicz, Markus Dominik Mueck, and Srikathyayani Srikanteswara. 2019. Energy demand prediction with federated learning for electric vehicle networks. In *2019 IEEE global communications conference (GLOBECOM)*. IEEE, 1–6.
[22] H Brendan Wang, Jintao Li, Yao Zhang, et al. 2019. Scalable and efficient federated learning via unbiased gradient estimation. In *Neural Information Processing Systems (NeurIPS)*.
[23] Kang Wei, Jun Li, Ming Ding, Chuan Ma, Howard H Yang, Farhad Farokhi, Shi Jin, Tony QS Quek, and H Vincent Poor. 2020. Federated learning with differential privacy: Algorithms and performance analysis. *IEEE transactions on information forensics and security* 15 (2020), 3454–3469.
[24] Yu Xu, Yan Li, Ming Sun, and Wei Li. 2021. Privacy-preserving machine learning for price prediction using federated learning. *IEEE Transactions on Emerging Topics in Computing* (2021).