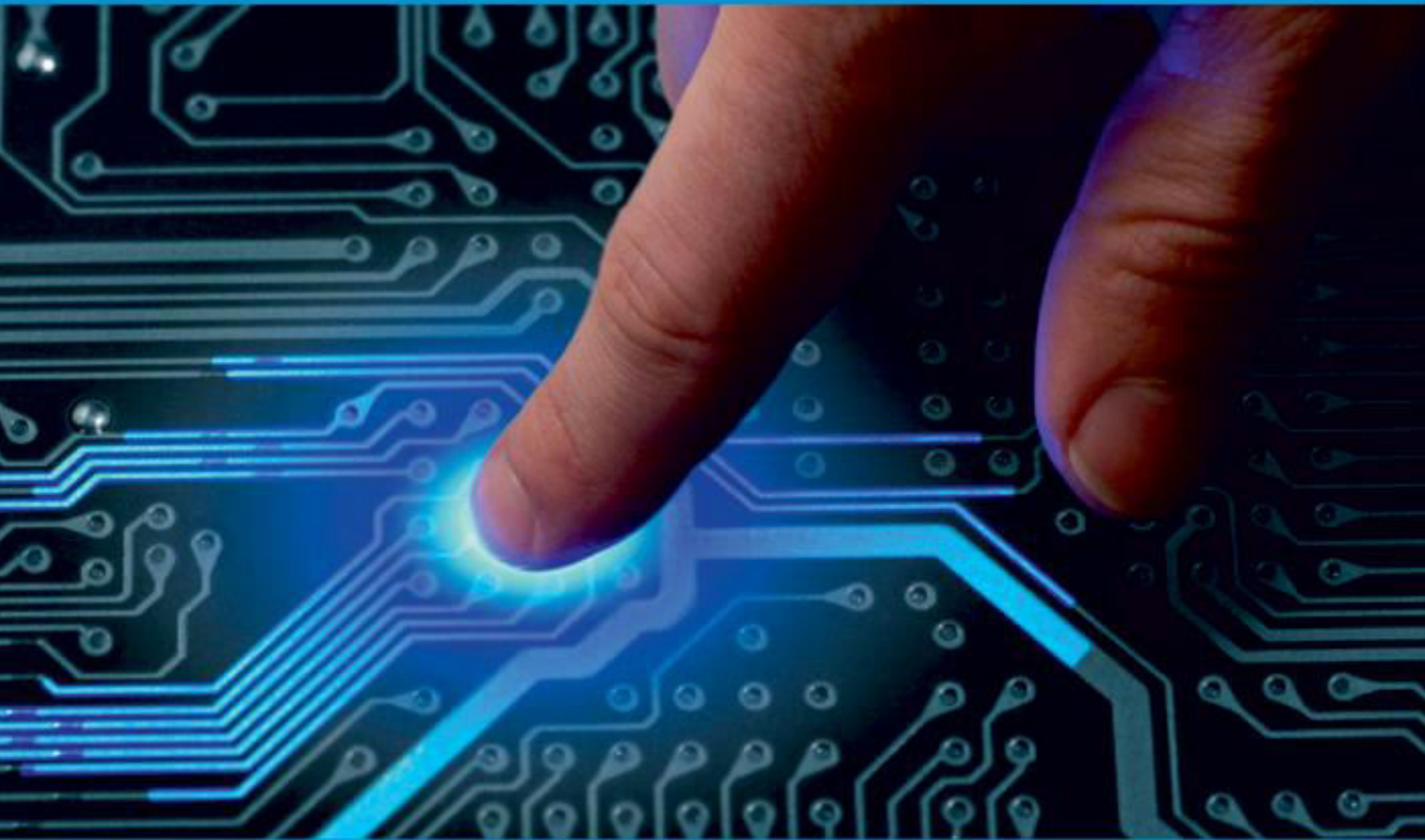
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 10, Issue 7, July 2022

Impact Factor: 8.165

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 7, July 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1007019 |

Mobile Crowdsensing Platform Using ML and Blockchain

Abitha A, Athira S, Megha Mathew, Mr. Karthik Raj S L

Student, Dept. of IS Engineering, The Oxford College of Engineering, Bangalore, Karnataka, India

Student, Dept. of IS Engineering, The Oxford College of Engineering, Bangalore, Karnataka, India

Student, Dept. of IS Engineering, The Oxford College of Engineering, Bangalore, Karnataka, India

Dept. of IS Engineering, The Oxford College of Engineering, Bangalore, Karnataka, India

ABSTRACT: Using mobile crowdsensing (MCS) to sense cyber - physical social systems i s an unique sensing scenario. By giving them rewards, MCS applications entice users to gather sensory data f rom the target area. In order to encourage people to join and provide sensory data, reward methods are essential. However, hostile task initiators, participants, and hackers might put sensory data and private information in grave danger while the MCS programmes carry out the incentive processes. This article suggests a novel MCS fram ework based on blockchain technology that protects privacy while securing the sensing process and the incentive mechanism. We provide more clarification on how human and machine intelligence might be combined in MCS .

KEYWORDS: Mobile crowdsensing; participatory sensing; task initiator; participant; reward mechanism

I. INTRODUCTION

Data gathered from sensing campaigns like sensor networks and crowd-sourcing is a major component of new Internet of Things (IoT) applications and services. Traditional sensor networks place sensors on the ground to collect data on a range of human life-related topics, but they have never realised their full potential or been successfully applied in the real world. This is because there are still many problems to be handled, like expensive installation costs and poor geographical coverage. Using the strength of mobile technology, Mobile Crowd Sensing (MCS) introduces a new sensing paradigm. The data gathered on the ground along with the assistance of the cloud, where data fusion occurs, make MCS a flexible platform that may frequently replace static sensing infrastructures and enable a wide variety of applications. MCS is a novel sensing paradigm that enables regular people to contribute data detected or generated from their mobile devices, combines and fuses the data in the cloud for gathering crowd intelligence, and provides services that are centred on the needs of the people.

A growing number of mobile device owners can share sensed data through MCS, and in return, the owners receive rewards for their participation. Local news, noise levels, traffic conditions, and social knowledge are just a few examples of the different types of data that could be captured from smart mobile devices. Due to the movement of a high number of mobile users, there is a diverse spatial coverage. The introduction of MCS, however, also brings with it a number of important difficulties, including cross-space data mining, maintaining privacy, and providing high- quality data. Poor data could make it harder to deliver high-quality services and possibly harm MCS systems. The mobile crowd sensing paradigm creates several and distinct research issues, such as different data collection methods, appropriate incentive systems, the quality of user-contributed data, cross-space data fusion, and more. Several techniques have been put forth to increase the quality of the data (QoD) in MCS, including estimate and prediction of the sensing data as well as statistical processing to find and eliminate outliers in the sensing values.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |
|| Volume 10, Issue 7, July 2022 ||
| DOI: 10.15680/IJIRCCE.2022.1007019 |

II. RELATED WORK

In [1] a fully distributed crowd counting protocol for cities with high crowd densities. UrbanCount relies on mobile device-to-device communication to perform crowd estimation. Each node collects crowd size estimates from other participants in the system whenever in communication range and immediately integrates these estimates into a local estimate. The objective of UrbanCount is to produce a precise mapping of the local estimate to the anticipated global result while preserving node privacy. In this work, we presented UrbanCount, a fully distributed protocol for crowd counting via device-to device communication, which is suitable for operation in urban environments with high node mobility and churn. But,this system did not focus to evaluate other scenarios in a realistic testbed, including an investigation of interference and path-loss effects as well as communication technology specific impacts [2]. In this paper, we study the physical crowd-sensing problem and draw the connection to the vertex cover problem in graph theory. Since finding the optimal solution for minimum vertex cover problem is NP-complete and the well-known approximation algorithms do not perform well with under crowdsensing scenario, we propose the notions of node observability and coverage utility score and design a new context-aware approximation algorithm to find vertex cover that is tailored for crowd-sensing task. But, Limited features. In [3] this paper, we propose a Mobile Crowd Sensing application based on Community Information Centric Networking to collect opportunistic sensing data in limited area where it restricts radius of Bluetooth Low Energy beacon. The application has more valuable features by comparing with common Mobile Crowd Sensing one. First is to support data integrity and utilize simple communication model according to IP-less communication through common CICN features. Secondly, to gather sensing data by using a name including BLE beacon Identifier.In [4] In this paper, we propose effSense—an energy-efficient and cost-effective data uploading framework, which utilizes adaptive uploading schemes within fixed data uploading cycles. In each cycle, effSense empowers the participants with a distributed decision making scheme to choose the appropriate timing and network to upload data. In [5] this paper, we study a critical problem in MCS systems, namely, incentivizing worker participation. Different from existing work, we propose an incentive framework for MCS systems, named Thanos, that incorporates a crucial metric, called workers' quality of information (QoI). Due to various factors (e.g., sensor quality, environment noise), the quality of the sensory data contributed by individual workers varies significantly. Obtaining high quality data with little expense is always the ideal of MCS platforms. In [6] this work, we propose to use blockchain technologies and smart contracts to orchestrate the interactions between mobile crowdsensing providers and mobile users for the case of spatial crowdsensing, where mobile users need to be at specific locations to perform the tasks. Smart contracts, by operating as processes that are executed on the blockchain, are used to preserve users' privacy and make payments.

III. PROPOSED ALGORITHM

A. *Phase 1*:

Requirement of the data collection will be performed using Trust-Evaluation with Data_Set.csv.

B. Phase 2:

Three processes will be used during technology adaption, such as:

a) Feature extraction:

Feature extraction is the process of extracting all trust evolution values from datasets, such as healthcare, employment, and traffic data, utilising the terms frequency and inverse document frequency.

b) Preprocessing:

Support Vector Machine (SVM), Random Forest (RF) and Gaussian Nave Bayse are some of the various algorithms used to process the dataset during preprocessing (NB). In a trust features model called "Best Model.pkl," the machine learning algorithm GNB creates the best scores for the test and train datasets, including accuracy, precision, f1, and recall scores.

i. Support Vector Machine: It selects the data points from a collection whose removal would changethe location of the dividing hyper plane that are closest to the hyper plane.They can therefore be regarded as the crucial components of a data set.

Example Code:

From sklearn.svm import SVCclf = SVC(kernel='linear') clf.fit(X, y)

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |
|| Volume 10, Issue 7, July 2022 ||
| DOI: 10.15680/IJIRCCE.2022.1007019 |

We have our points in X and the classes they belong to in Y.
To predict the class of new dataset: prediction = clf.predict([[0,6]])
ii. Random Forest: A supervised machine learning approach based on ensemble learning is known asrandom forest. Additionally, the random forest technique can be used for both classification and regression problems. It mixes numerous algorithms of the same type.
Step 1 − Start with the selection of random samples from Data_Set.csv.
Step 2 − Next, this algorithm will construct a decision tree for every sample. Then it will get theprediction result from every decision tree.
Step 3 − In this step, voting will be performed for every predicted result.
Step 4 − At last, select the most voted prediction result as the final prediction result.
iii. Naïve Bayes Algorithm: It is a machine learning model that is used for massive amounts of data, and it performs NLP tasks like sentimental analysis with excellent results. A quick and simple classification algorithm is used.
Calculating posterior probability equation:
$P(c/x) = P(x/c) P(c) P(x)$
Step 1: Convert the Data_Set.csv into a frequency table.
Step 2: Create Likelihood table by finding the probabilities like Overcast probability = 0.29 andprobability of playing is 0.64.
Step 3:Calculate the posterior probability for each class. The class with the highest posteriorprobability is the outcome of prediction
c) Classification:
Using "Best Model.pkl," classification can be properly performed on both test and training data to match categories including traffic, healthcare, and employment.
C. Phase 3:
Various trust files were tested, and it was discovered that a new classification method existed. If the process data is compared with features like "Best Model.pkl," then it processing with testing data after the process and display the result. In Results analysis are provide real time detect the matching category above of 90% like Healthcare, Traffic, and Job and bellow of 70% is un-matching category.

IV. PSEUDO CODE

Step 1: Collection of data for data_set.csv and training the machine learning model.Step 2: Test the machine learning model by passing X_Test, Y_Test

Step 3: After we train the four machine learning algorithm we obtain more accuracy in support vector machine, which is then loaded into bestmodel.pkl

Step 4: Task initiator post the query in the android app:
i. Feature Extraction:
TF-IDF = TF∗IDF
ii. Classification:
The ML model classify the query using bestmodel.pkl
iii. Based on the classification query will get accepted or rejected.

Step 5: Participant can comment on the task obtained and the comments are validated by ML Model.Step 6: On validation of comment, Task initiator receives the comments.

Step 7: The participant’s reputation and reward increases or decreases based on acceptance or rejectionfrom Task Initiator

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 7, July 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1007019 |

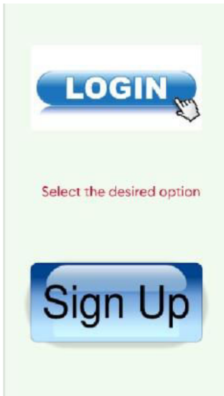
Step 8: Reward allocations are maintained by Ganache, by assigning block chain addresses for each users.Ethers are either added or subtracted.

V. SIMULATION RESULTS

1. Training Model: The Data_set.csv was created and trained for four different algorithms and the result was obtained for the algorithm along with its respective accuracy for the given data set. Where it was seen that the support vector machine algorithm had the highest accuracy. Therefore it was considered the best model. pkl.
2. User Interface: Initially the user needs to signup as either the task initiator or the participant by providing necessary data and uploading the certificate. Then users can log in using their credentials. As a task initiator, the user has the option to post the query or view the comment. The task initiator is also responsible for accepting/rejecting the answer posted, accordingly reward is allocated. Whereas as a participant login it will have the option to view reputation, view task, and view rewards.
3. Blockchain: Ganache assigns blockchain addresses for each user and maintains the ethers.

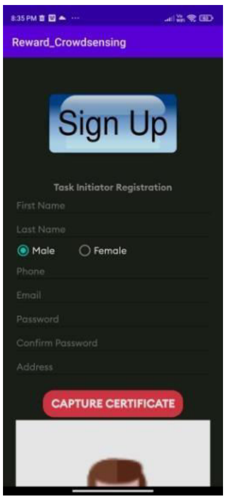
Welcome Activity

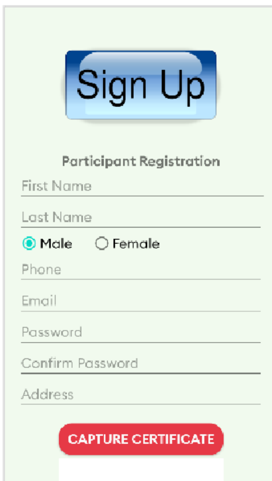
Once the mobile app starts provide us twooptions either signup or login



Participant and Task initiator Signup

The participant and task initiator can signup from the mobile app. While registration he/she should provide the personal details along with identity proof.





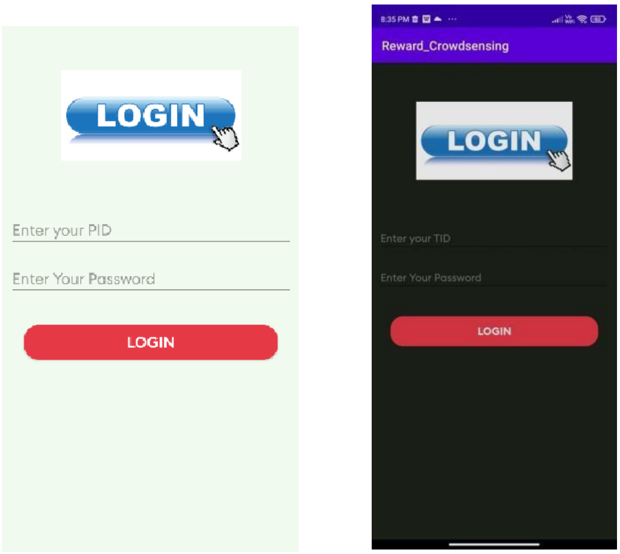
| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 7, July 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1007019 |

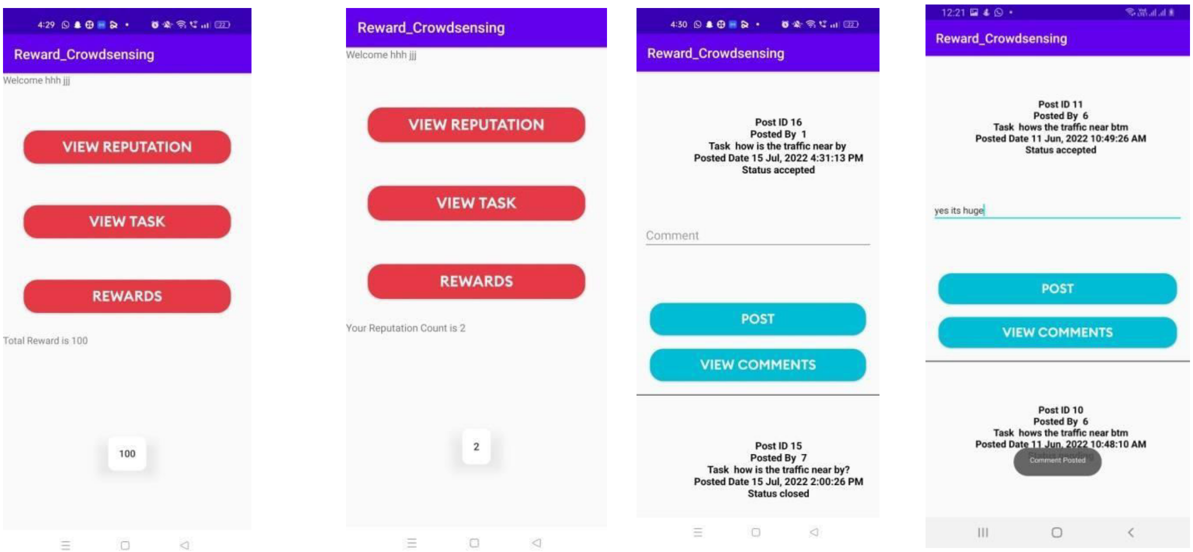
Participant and Task Initiator Login

Participant and task initiator should provide login id and password. The login credentials are verified by the server.



On Participant LogIn :

Participant can view their Reputaion, Task and Rewards. After viewing the Tasks, Participant can post their comments and the details are saved in the blockchain.



Post task

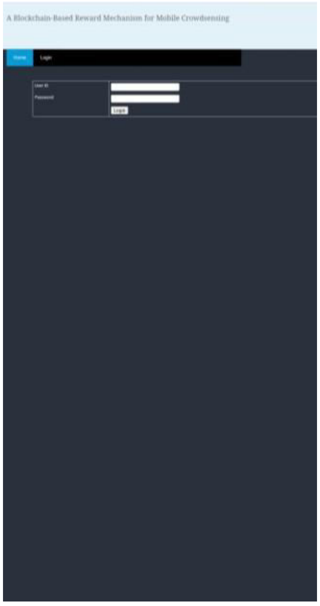
Task initiator can post the queries. Each query is saved in the blockchain. The posted query is processed and using machine learning algorithm the category is predicted. Then task initiator can view the comments commented by the participants.

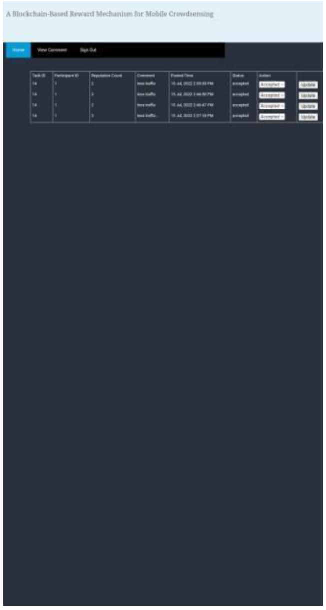
Also can accept or reject the comment.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 7, July 2022 ||

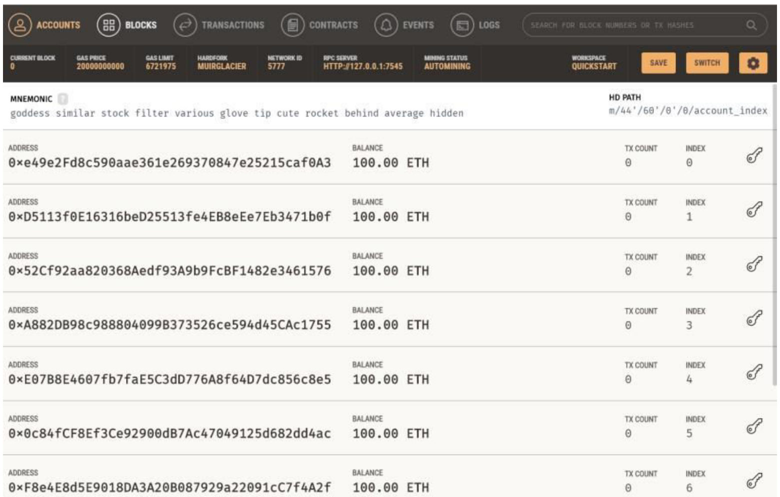
| DOI: 10.15680/IJIRCCE.2022.1007019 |





Blockchain nodes using ganache

The blockchain addresses are linked with the users.



VI. CONCLUSION AND FUTURE WORK

In this project, we presented an ML-based incentives system for mobile crowdsensing that can be used to reward participants who submit comments on the task that is begun by task initiator in crowdsensing applications. With the aid of our system, participants can use their smart devices to input sensory data and receive incentives in the form of ethers. To help us verify the users of the application and the sensing task, we designed a set of smart contracts for this project, including Participant, Task, Task Initiator, and Comment contracts. We made transactions involving ethers, the primary token of our blockchain, which are recorded and confirmed in the Ethereum blockchain, using the Ethereum blockchain to operate smart contracts without the need for a third party. Following task completion, these tokens are redeemed based on user demand. Our protocol, which is significant, ensures the integrity of the trade because neither the task initiator nor the participants may defraud one another. As opposed to the complex smart contracts employed in past

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 7, July 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1007019 |

research, we exclusively concentrated on straightforward Pay-to-ScriptHash transactions, guaranteeing the applicability of our strategy in real-world deployments.

REFERENCES

1. Peter Danielis, Sylvia T. Kouyoumdjieva and Gunnar Karlsson, UrbanCount: MobileCrowd Counting in Urban Environments ,2017.
2. Phuong Nguyen, Klara Nahrstedt,' Context-aware Crowd-sensing in Opportunistic Mobile Social Networks Author, 2015.
3. Taewan You, Muhammad Umair, Yong-Gen Hong,' Mobile Crowd Sensing based on CICN, 2017.
4. Leye Wang, Daqing Zhang, Member, IEEE, Zhixian Yan, Member, IEEE, Haoyi Xiong, Member, IEEE, and Bing Xie A Novel Mobile Crowd-Sensing Framework for Energy-Efficient and Cost-Effective Data Uploading ,2015.
5. Haiming Jin, Member, IEEE, Lu Su, Member, IEEE, Danyang Chen, Hongpeng Guo, Klara Nahrstedt, Fellow, IEEE and Jinhui Xu ,' Incentive Mechanism with Quality Awareness for Mobile Crowd Sensing, 2018.
6. Dimitris Chatzopoulos , Sujit Gujar&, Boi Faltings , and Pan Hu, Privacy Preserving and Cost Optimal Mobile Crowdsensing using Smart Contracts on Blockchain Author, 2018.

BIOGRAPHY

Ms. Abitha A She is currently doing B.E in Information Science and Engineering department at The Oxford College of Engineering, Bangalore, Karnataka.

Ms. Athira S She is currently doing B.E in Information Science and Engineering department at The Oxford College of Engineering, Bangalore, Karnataka.

Ms. Megha Mathew She is currently doing B.E in Information Science and Engineering department at The Oxford College of Engineering, Bangalore, Karnataka.

Mr. Karthik Raj S L he is working as Assistant Professor in Information Science and Engineering department at The Oxford College of Engineering, Bangalore, Karnataka.

INNO SPACE

SJIF Scientific Journal Impact Factor

Impact Factor: 8.165

doi crossref

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

निस्केयर NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

Scan to save the contact details