A low-cost TinyML model for Mosquito Detection in Resource-Constrained Environments

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ABSTRACT

Yearly, more than 200 million malaria cases are recorded worldwide. Most of these cases are witnessed in less developed countries as the environments are not well-maintained, which forms breeding places for mosquitoes. Female mosquito-anopheles is responsible for malaria infection, dengue, chikungunya, and zika. Developing countries struggle to fight diseases; malaria still claims more than 400,000 lives annually. One current way to keep away anopheles mosquitoes is using commercially available electric liquid mosquito repellents, which can adversely affect the human body when used for extended periods. Furthermore, energy and sprays are wasted as they constantly work even without the presence of anopheles mosquitoes. We propose a low-cost IoT-based TinyML model that intelligently discharges the mosquito repellent when an anopheles mosquito is in the room. First, we prove the concept by exploring two lightweight deep learners with a 1D Convolution Neural Network (1D-CNN) and 2D Convolution Neural Network (2D-CNN) to classify raw sounds from mosquito wingbeats. We adopted a Leaky ReLU in building the 1D-CNN to speed up training and improve classification performance. Furthermore, we adopted batch normalization to avoid degradation and vanishing gradient problems. We implemented the experiments in an Edge impulse platform. Each of the CNN models recorded stable classification performance during the proof of concept study, while the 1D-CNN took less time and computing resources in training, validation, and testing. As we aimed to propose a low-cost solution, we evaluated the performance of the 1D-CNN-based prototype in the actual deployment by playing mosquito wingbeat sounds on a laptop which we placed next to it in intervals of 0.5, 1.0, 1.5, 2.0, 2.5, and 3 meters. The model showed promising results across distances and thus could be used to chase away mosquitoes in a room of small to medium size.

CCS CONCEPTS

• **Computer systems organization → Sensors and actuators**; • **Computing methodologies → Neural networks**; • **Hardware → Renewable energy**.

KEYWORDS

TinyML, Mosquito detection, Artificial intelligence, Internet of Things

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1 INTRODUCTION

Malaria *Plasmodium falciparum* is a preventable and curable disease [4] that is caused by parasites transmitted to people through the bites of infected female Anopheles mosquitoes [26]. According to the World health organization, there were an estimated 241 million malaria cases worldwide in 2021. Furthermore, during that year, the estimated number of malaria deaths stood at 627 000 [15]. Out of those numbers, the African region is the worst hit by the malaria burden, and in 2020, malaria cases accounted for 95% of the cases globally. More worrying, 96% of the global malaria deaths were recorded in Africa [10]. This trend is unpleasant, as the diseases exacerbate poverty by preventing people from working to make a living. Thus, diseases have been attributed to a factor in the low growth rate of many African countries [1]. In Sub-Saharan Africa, the most common methods of prevention against malaria include the use of mosquito bed nets sprayed with insecticides and using insect repellents [2, 25]. Although bed nets are relatively cheap and efficient, they only work when people are in bed. On the other hand, mosquito repellents are expensive as they require insecticides even when there are no anopheles mosquitoes [3]. The continuous release of insecticides into the environment is unhealthy and leads to environmental pollution [10]. Therefore, detecting the presence of anopheles mosquitoes in a specific home is crucial before insecticide sprays can be utilized. There are three main species of mosquito: Anopheles, Aedes, and Culex. Aedes cause the following diseases: chikungunya, dengue, yellow fever, and zika, while culex causes Japanese encephalitis and West Nile fever. The Anopheles mosquitoes cause malaria infection, dengue, chikungunya, and zika.

The TinyML approach is a branch of Machine Learning (ML) where ML models are offloaded to run on low-resourced devices. On the other hand, the Internet of Things (IoT), where sensors, actuators, and other "things" communicate, enables the deployment of the TinyML. The main aim of TinyML is to reduce the cost of computations and make ML models usable in low-scarce environments [19]. In recent years, the TinyML approach to Artificial Intelligence (AI) has gained much popularity due to the need to reduce the cost of computations and make it universally accessible [19]. In this study, we explore the applicability of an ultra-TinyML model in detecting anopheles mosquitoes and the subsequent release of mosquito repellents.

1.1 Problem Statement

Mosquito repellents are composed of chemicals that are harmful to human health [13]. Insecticides, the main component of mosquito repellent, may cause undesirable hazardous interactions with biological systems and potentially generate harmful effects [5, 28]. Furthermore, insecticides are known to be toxic to the environment, challenging the "One-health" goal [9]. Additionally, the electrical mosquito repellant is always on even in the absence of anopheles mosquitoes; thus, much energy is consumed, making the solution expensive and unusable, especially in developing countries [19]. To solve the challenges, we propose a TinyML model that intelligently detects anopheles mosquitoes based on their wingbeat sounds and releases mosquito repellents.

1.2 Contributions

This study proposes a low-cost IoT-based model for monitoring anopheles mosquitoes and releasing mosquito repellents intelligently. Our main contributions are twofold; first, we performed the feasibility of applying 1D-CNN and 2D-CNN in detecting mosquitoes based on their wingbeats. We compared their performances in accuracy, precision, f-measure, recall, latency, main memory, and flash memory usage. Second, we deployed the 1D-CNN with the IoT to detect anopheles mosquitoes and activate the release of mosquito repellents. We explored the energy and cost saved when the model was used.

The rest of the paper is organized as follows: we provide related work of the study in Section 2 and methodology in Section 3. Section 4 reports on the evaluation of the proposed model, while Section 5 discusses the deployment of the proposed model for real-time mosquito detection. We provide discussions and lessons learned in Section 6. Lastly, we provide conclusions and recommendations for future research in Section 7.

2 RELATED WORK

The past decade has witnessed unparallel advancement in computing power coupled with a reduction in the cost of computing devices. This has made a large data volume available across domains, making ML applications a reality. Research on the application of Machine Learning (ML) and the Internet of Things (IoT) in malaria detection follows three main research directions. The adoption of acoustic sensors, odor-based sensors, and the use of optical sensors [12, 16]. All these directions have shown much promise in their proof of concepts. However, using optical and odor-based sensors is expensive and power-hungry [16]. In this paper, we propose a low-cost solution. Thus we focus on the prior studies that have proposed using acoustic sensors, which have been shown to lead to low-cost solutions.

Mukundarajan et al. [24] proposed using mobile phones to record mosquito repellent for high-throughput mosquito surveillance. Their proposal to use mobile phone microphones as acoustic sensors makes the solution usable even in resource-constrained environments, as mobile devices have been integrated into almost everyone's lives. They have yet to engineer the solution in terms of energy management to make it ready for deployment. In [11], the authors explored the possibility of using ML to detect Aedes aegypti mosquito species. Since their model was designed for resource-scarce environments, it needed to be more lightweight. Authors of [30] used Edge Impulse and an Arduino Nano 33 to classify three species of mosquitoes (anopheles, Aedes and Culex). They have not engineered the solution to make it field-ready in terms of power consumption and flexibility, and no communication option is presented. Showing the result on display is helpful for local populations but does not allow for long-term research on mosquito presence.

Authors in [34] performed a feasibility study on applying a Deep Learning (DL) model and the following standard machine learners in counting mosquitoes and putting them in categories: K-Nearest Neighbours, support vector machines, random forests, naive Bayes, and linear regression. Unsurprisingly, the DL mode outperformed the other models, and linear regression recorded the lowest results. Work that inspired us in this direction is presented in [1], where they proposed a TinyML for classifying mosquitoes based on their species. They considered two species of mosquito, and their model recorded promising results. They further performed experiments on the power consumption of various microcontrollers to produce an ultra-low power model. They intend to deploy their models to classify mosquitoes in their future study. Research in [6] proposed a 2D CNN for detecting anopheles mosquitoes and the appropriate release of mosquito repellents. In contrast, in this study, we propose the adoption of a 1D CNN, which is lighter than the 2D CNN the researchers presented. This will reduce the cost of the solution further. They implemented their approach in traditional Graphical Processing Units (GPUs), which requires many resources that are not readily available in resource-constrained environments. In this approach, we implemented our proof of concept in an Edge impulse platform, which is open and appropriate in developing countries.

The literature clearly shows that the area is attracting justified attention from researchers. Most research aims to identify and count mosquito species to inform mitigation measures. These models can also build prevalence predictions based on seasons. However, only a few mosquito detection datasets exist; thus, it requires action, especially with crowdsourced citizen data. Additionally, the literature suggests that sub-Saharan Africa accounts for more than 90% of the global cases [10], so the proposed solutions should be low-cost to make them uniformly affordable, especially in these resource-scarce countries. More encouragingly, the advent of cloud platforms for performing ML training and deployment is accelerating research in the area as it provides computing as a service in machine learning. Some works that we reviewed and reported have adopted the Edge impulse cloud platform to train and deploy their ML models with promising results. This trend is expected to continue, and, more importantly, there will be more implementation of ML models in resource-scarce environments.

3 METHODOLOGY

We propose a four-stage approach to developing a low-cost smart mosquito repellent model: First, as we envisioned to present a low-cost and low-power solution that could run on embedded low-cost devices, we performed a feasibility study using TinyML-based models based on 1D-CNN and 2D-CNN architectures to classify mosquito species. We compared the performance of the two architectures in classifying an open-source dataset regarding classification performance, main memory, and flash memory usage. Second, we performed a feasibility study using TinyML-based models based on 1D-CNN and 2D-CNN architectures to classify mosquito species. We compared the performance of the two architectures in classifying an open-source dataset regarding classification performance, main memory, and flash memory usage. Third, we performed a feasibility study using TinyML-based models based on 1D-CNN and 2D-CNN architectures to classify mosquito species. Fourth, we deploy the 1D-CNN model with Arduino Nano 33 for real-time detection of mosquitoes and the intelligent release of mosquito repellents. We explored using Renewable Energy Sources (RES) to power the solution and performed duty cycling on the model to save on energy consumption.

3.1 Selection of datasets

We examined various open-source mosquito wingbeats datasets that could be used in training deep learners to classify mosquitoes. We selected a wingbeat dataset [21] as it has been selected as a standard dataset in Kaggle contests. Additionally, the data was collected with low-cost smartphones and professional-grade recording devices; thus, they could be used to train models that can detect wingbeats recorded in various acoustic sensors. The dataset is rich as it was collected in Tanzania, Kenya, the United States of America, and the United Kingdom, representing both developing and developed countries' environments. It makes the model general enough to be usable across different geographical regions. The dataset contains three common species of mosquitoes. We introduced a class of domestic environment sounds, including human speakers, human activity, television, household appliances, silence, and unidentifiable sounds, to enable the models to learn other categories of sounds which are not mosquito related but are present in a home environment. We used the dataset's 80/20 training/test ratio, which has been widely used in the state of the art. Furthermore, we used 20% of the training dataset to validate the model. Table 1 shows the ratio of training, validation, and testing used in this study.

Table 1: The classes on the datasets that we used in the study

Class	Training	Validation	Testing
Aedes albopictus	640	160	200
Aedes aegypti	640	160	200
Culex quinquefasciatus	640	160	200
Domestic environment	640	160	200
Culex pipiens	640	160	200
Anopheles Arabiensis	640	160	200
Anopheles gambiae	640	160	200
Total	**4480**	**1120**	**1400**

3.2 Model Design and Training

We explored the applicability of 2D and 1D CNN TinyML architectures in detecting mosquitoes based on their wingbeats. The Tiny-ML models can run on a low-cost, ultra-low-power device that can be implemented in resource-constraint devices [20]. The architecture of the 2D CNN network is presented in Fig 1 (a). It has only two convolutional layers (CLs), which was much reduced compared to the classical models, including ResNet [29], VGG [22], Inception [27] among others. The architecture of the 1D CNN network is shown in Fig 1 (b). We reduced the CLs of the CNN to two, and instead of max-pooling layers, we adopted batch normalization to ease the network's training and avoid the degradation and vanishing gradient problems [33]. Each of the two CLs in the 1D-CNN had a filter size of three and stride one. Additionally, the architecture had two batch normalization (BN) layers and an identity shortcut where the models skipped some of the layers of the CNN when the parameters were accurately set to avoid the overfitting problem. We used a Leaky ReLU as an activation function as it speeds up training and makes its mean activation function close to 0 [23]. The Leaky ReLU also performs well in acoustic-based tasks [17].

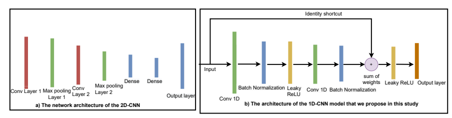

Figure 1: The architectures of the 1D-CNN and 2D-CNN models that we explored in this study

To perform training, we set the learning rate at 0.001 with a batch size of 100 and an epoch of 60. We present the training progression rate of the CNN models in terms of accuracy and loss in Figure 2. The 1D-CNN registered its maximum accuracy at epoch 28, while the 2D-CNN achieved it at 30 epochs. The 1D-CNN model took a shorter time to attain its peak accuracy as the ReLU activation function, batch normalization, and identity shortcut accelerated the training. Furthermore, the 2D-CNN had increased parameters for training compared to the 1D-CNN. However, the training and validation accuracy did not differ significantly for the two CNN models and showed stable results. The 1D-CNN performed better in loss and converged faster than the 2D-CNN as the model applied the identity shortcut to skip similar patterns in data and thus could not suffer from overfitting. More interestingly, the difference between the training and the validation accuracy is minimal in 1D-CNN compared to the 2D-CNN model. This implies that the 1D-CNN did not suffer from overfitting, as the identity shortcut allowed the network to skip some layers when the weights were optimal. This makes the network not memorize but learn the patterns in data. Additionally, the accuracy and loss curves of the 1D-CNN were smoother than those of the 2D-CNN, as there were fewer parameters to train in the 1D-CNN network. Furthermore, batch normalization that we used in designing the 1D-CNN eases the training of the ML models. Therefore, it was cheaper to train the 1D-CNN and more stable in performance. Additionally, the 2D-CNN took more epochs to converge than the 1D-CNN, as the additional parameters in 2D-CNN require more learning time. However, the 2D-CNN registered better results in validation and training accuracy as the added parameters in its network improved the classification performance. During the training, validation, and testing of the CNN models, we saved about eight milliseconds of CPU time when we compressed the model from the 2D-CNN to the 1D-CNN using the pruning techniques [31] and saved the RAM usage by more than 4.5K, which significantly freed the main memory for other applications.

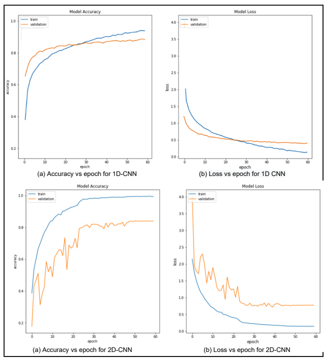

Figure 2: The accuracy and losses of the 2D and 1D deep learners in training and validation

3.3 Model Implementation

The architecture of the proposed model to monitor anopheles mosquito and release mosquito repellent in real time is presented in Fig. 3. The system had a microphone node attached to an Arduino Nano 33 device. The system is connected through Wi-Fi technology to the fog servers. Notice that in our solution, we utilized the Edge and fog environments.

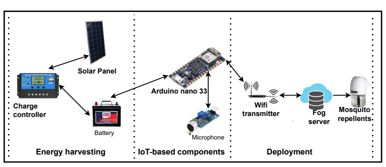

Figure 3: System architecture for the IoT-based smart mosquito repellent model

3.3.1 Resources. We submitted quotations for electric mosquito repellent to three major supermarkets in Eldoret City, Kenya: Naivas, Quickmart, and Khetia's. Based on received proforma invoices, Mortein mosquito repellent had the lowest power rating and promised to last longer (30 nights). Thus we chose it for our experiments as we were focused on providing a low-cost and low-power solution that can be used in resource-scarce environments. The IoT-based hardware used in this experiment included Arduino Nano 33, with a 19 mA power rating, and a microphone from Elecbee, whose power rating was 0.5 mA. Furthermore, we had a micro SD card of memory size 16 GigaByte (GB) attached to the microcontroller and acted as an Edge server.

3.3.2 Energy harvesting. We harvested energy for use in lighting the room and also for powering the IoT solution. We took 12 hours, the longest time that the solution could be used, as the sunset occurs at 6 pm and sunrise is witnessed at 6 am in the Eldoret region. During this period, mosquitoes are active, and thus, repellents are used. The rating of an Arduino Nano 33 was 19 mA, while the rating of the speaker was 0.5 mA. Equation 1 gives the energy of the IoT-based solution used during the period.

$$IoT\_Energy = 0.09525w \times 12hours = 1.143wh \tag{1}$$

As we envision simulating real-condition in a home setup, lighting was needed in the room. Thus we harvest energy for use in lighting the room. The total energy that is required to power the bulb for 12 hours a day is given by equation 2:

$$Bulb\_energy = 15w \times 12hours = 180wh \tag{2}$$

The required energy to power the electric mosquito for 12 hours is given by equation 3:

$$Repellent\_energy = 5w \times 12hours = 60wh \tag{3}$$

The total amount of energy required by the components daily is given by equation 4:

$$Energy\_total = 180wh + 1.143 + 60wh = 241.143wh \tag{4}$$

Energy harvesting is affected by the efficiency of the components [14]. In this study, the battery's efficiency was 80% while the efficiency of the charge controller was 85%. Therefore the required energy to be harvested is given by equation 5:

$$PV\_array = \frac{241.143}{0.8 \times 0.85} = 354.6wh \tag{5}$$

The radiation time in a region affects the amount of PV-based energy that can be harvested [14]. We used the worst radiation season in the Eldoret region for a stable energy supply to our components, which occurs in August with an average of 5 hours daily [18]. Although mismatch factors also affect energy harvesting [8, 32], regions closer to the equator are not challenged by mismatch factors, which is the case for Eldoret. Hence a solar panel of more than 70.9 W could serve the model. We thus chose a solar panel of 80w more than the minimum of 70.9w. (equation 6).

$$Array\_Load = \frac{354.6wh}{5h} = 70.9w \tag{6}$$

Deep-discharge batteries are durable and work well with solar panels; thus, we selected them for our experiment. It allowed a maximum of 60% discharge levels and a voltage rating of 12V. Typical energy storage by the battery is given by equation 7:

$$Total\_energy = \frac{241.143wh}{0.6} = 401.9wh \tag{7}$$

Equation 8 presents the required battery rating. As a rating of 33.5 was not available in the market, we chose a battery with a 40 A/h rating as it was the nearest.

$$rating\_battery = \frac{401.9}{12v} = 33.5A/h \tag{8}$$

4 EVALUATION RESULTS

The average accuracy achieved by the 1D-CNN and the 2D-CNN models when evaluated based on the dataset discussed in Section 3.1 were 78.02% and 82.94% (Figure 4). Although the 2D-CNN outperformed the 1D-CNN, they did not differ significantly; they performed evenly well across the classes in the dataset. The sophisticated results of the 2D-NN model were due to the additional CNN parameters for decision-making. We observed the same trend when we evaluated the model based on precision, recall, and f-measure. However, both models recorded good results and proved that any of them could be implemented in actual deployment based on performance and cost issues.

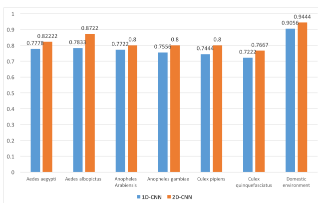

Figure 4: The comparison of the accuracy values obtained by the 1D-CNN and 2D-CNN models

5 DEPLOYMENT OF THE MODEL

Real-world evaluation of our model is not trivial, mainly because we cannot guarantee the presence of mosquitoes, especially not in the quantity we would need for evaluation. Thus, we adopted a slightly different approach. First, we evaluate the correctness and efficiency of the model itself to recognize mosquitoes. We did so by playing mosquito sounds at varying distances from the receiver. Second, we evaluated the energy consumption of our deployment compared to the traditional way of always turning on the mosquito repellent every night. Figure 5 (b) shows the prototype deployed in a bedroom in a house in Eldoret City, Kenya. The prototype was deployed to run for 50 nights, from 20th November 2022 to 8th January 2023. Additionally, we implemented a traditional electric mosquito repellent that we discussed in Section 3.3.1 in a different room in the same building (Figure 5 (a)) to act as a base. We turned them on from 6 pm to 6 am during the 50 nights to compare the energy consumed by the two models and the cost.

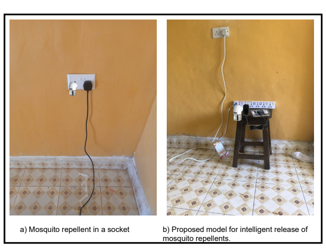

Figure 5: Deployment of the 1D-CNN model with the IoT for detection of anopheles mosquito and intelligent release of mosquito repellents.

5.1 Energy and Costs comparisons

The average time it takes an anopheles mosquito to bite after entering a room with moderate temperatures and the absence of mosquito repellent is 6.5 minutes [7]. Therefore, through intermittent computing, the model should be awake at least every 6.5 minutes to "listen" to mosquito wingbeats. Thus, we performed duty-cycling on the IoT-based mosquito repellent model, which was turned on every 5 minutes each for 10 seconds to listen for anopheles mosquitoes.

We compare the amount of energy consumed by the proposed prototype to the traditional approach in Table 2. In the conventional method, mosquito repellents were turned on throughout the night from 6 pm to 6 am. Therefore, the energy consumed by the traditional mosquito repellent was much larger than that consumed by the proposed solution, which had undergone duty cycling. Duty cycling resulted in saving about 2995 W amount of energy during the 50 nights of deployment. The total amount of energy that the proposed model used was 4.2179 W. These results are significant as they proved the viability of intermittent computing in the deployment of computing tasks in resource-scarce environments. Finally, during the 50 nights of implementation, the traditional approach where a mosquito repellent worked from 6 pm to 6 am every night resulted in using three mosquito repellents. On the other hand, the IoT-based solution used only one mosquito repellent. Therefore, these findings showed that using the IoT-based solution resulted in the economical usage of mosquito repellents, which resulted in saving on cost and reducing the pollution of the environment by the insecticides in the mosquito repellent.

Table 2: Energy consumption comparison of the traditional approach and the IoT-based mosquito repellent model..

Week	Proposed approach (W)	Traditional approach (W)
1	**0.78181**	600
2	**0.86515**	600
3	**0.89293**	600
4	**0.73225**	600
5	**1.00405**	600
Total	**4.2179**	3000

Week 1: 20th -29 Nov 2022 Week 2: 30 Nov-9th Dec 2022
Week 3: 10-19 Dec 2022 Week 4: 20-29 Dec 2022
Week 5: 30 Dec-8 Jan 2023

5.2 Evaluation of the model during deployment

To further evaluate the performance of the 1D-CNN model in its deployment environment, we played unseen mosquito wingbeat sounds [1]. The classes of the dataset were Aedes aegypti, Aedes albopictus, Anopheles arabiensis, anopheles gambiae, Culex quinquefasciatus, and domestic environment. After downloading the sounds of the wingbeats, we played 50 of them in each class on a laptop placed next to the mosquito repellent at intervals of 0.5

[1]https://www.kaggle.com/code/potamitis/the-wingbeat-signal/data

to 3 meters at intervals of 0.5. The model's performance based on precision and recall is presented in Figure 6. The model produced excellent precision and recall values when the distance between the model and the speaker delivering the wingbeats sounds was between 0.5-1.5 meters. As the length increased from 2.0-3.0 meters, the model's performance reduced. When the distance between the laptop speaker playing mosquito wingbeats sounds, and the IoT-based model grew, the noise in the environment overpowered the mosquito wingbeats sounds. However, the precision and recall values at the furthest distance, 3.0 meters, were still good enough and showed the model's stability and usability in chasing anopheles mosquitoes in small to medium-sized rooms. However, the model's performance may increase or decrease depending on the noise in the deployment environment.

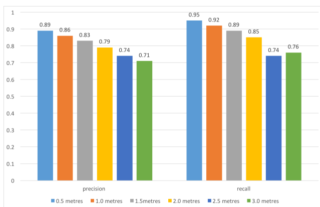

Figure 6: Evaluation of the 1D-CNN model in real deployment based on precision and recall

Furthermore, when the model was evaluated based on f-measure and accuracy, they showed a similar trend as reported during evaluation based on recall and precision. The performance reduced as the distance between the source of the mosquito wingbeats and mosquito repellent increased (Figure 7). However, the model showed good classification performance across distances and confirmed that the model could detect anopheles mosquitoes in its actual deployment.

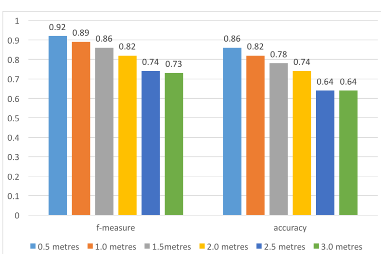

Figure 7: Evaluation of the 1D-CNN model in real deployment based on f-measure and accuracy

6 DISCUSSIONS AND LESSONS LEARNED

This study explored two TinyML models, 2D-CNN and 1D-CNN, for developing an intelligent mosquito repellent. We trained and evaluated them using an open-source mosquito wingbeat dataset. We further compared them in terms of performance and resource usage. The 2D-CNN model performed slightly better than the 1D-CNN model, although both models recorded promising results across the metrics. This was expected as the 1D convolution model had fewer parameters than the 2D-based DL model. The same observation has been made by other researchers, including [34], where the performance of the DL-based model reduced with the reduction in the CNN parameters. However, both models generally recorded good classification performance across the metrics, showcasing that any of them could be used in the classification task. As our main goal was to develop an ultra-Tiny model that could work in a resource-constrained environment regarding power and cost, we selected the 1D-CNN for exploration in an actual deployment. The adoption of the ID-CNN resulted in reduced memory usage, CPU time, and flash memory usage. We expected it as we significantly reduced the number of parameters involved in the prediction. The latency was also reduced as the decision-making process took less time as it applied fewer layers than more complex architectures.

More interestingly, we evaluated the 1D-CNN in its real-deployment environment by playing the sounds of unseen mosquito wingbeats on a laptop at intervals of 0.5, 1.0, 1.5, 2.5, and 3.0 meters. The model produced promising results across distances and confirmed that it was trained well and did not suffer from overfitting. The prototype was powered by a PV-based energy source, making the solution autonomous and usable in areas not connected to the grid. The application of duty cycling ensured that we saved much energy and also ensured we saved on repellent usage. This reduced the cost of the solution and the environmental pollution by only releasing the mosquito repellents when necessary.

We can briefly highlight some of the lessons that we learned as follows. First, reducing the complexity of the CNN model results in a reduction in the classification performance. Second, when a DL architecture is simplified, it saves CPU time, main memory, and flash memory usage. This potentially results in the saving of resources. However, DL models must be more complex for improved performance, increasing the computation cost. Thus, there should be a trade-off between performance and cost reduction. Third, there is no ground truth for developing DL models. It is up to the model designers to understand their computation needs and constraints. A good model delivers on performance and works within the constraints. Fourth, intermittent computing, when modeled correctly, reduces energy consumption by the model, reducing the cost of the solution. However, consideration should be taken to ensure the model's performance is not compromised. In our case, prior studies showed that mosquitoes would take an average of 6.5 minutes to bite after discovery. Therefore, we used a duty cycle of 5 minutes which was less than that time. Fifth, PV-based energy harvesting is an effective way of generating energy when done correctly with careful consideration of solar mismatch factor, distance from the equator, peak solar radio, and battery effectiveness.

7 CONCLUSIONS AND FUTURE WORK

In this paper, we have explored 1D-CNN, and 2D-CNN architectures, which we trained with an openly available dataset on mosquito wingbeat sounds in the edge impulse platform. The models showed promising results across the dataset and did not differ significantly. We explored their resource consumption on the edge impulse platform, where 1D-CNN used fewer Random Access Memory (RAM) and flash memory resources. Thus we adopted the ID-CNN architecture in the actual deployment for anopheles mosquito detection and intelligent mosquito repellent release. The 1D-CNN model produced promising results when evaluated in an unseen dataset in its deployment environment. Thus the model is expected to be usable in its deployment environment, as evidenced by its superior classification results. We powered the prototype using a Photovoltaic (PV) energy source to make the solution usable in areas not connected to the grid and advance efforts of using green energy solutions. Additionally, we applied duty cycling, where the prototype was designed to sleep and wake up every 5 minutes to listen to the anopheles mosquitoes. This ensured that we saved much energy making the solution cheap. During the actual deployments in the 50 nights, the proposed prototype used one mosquito repellent, whereas we used three mosquito repellents in the traditional approach. Furthermore, the proposed method resulted in fewer insecticides being released into the environment, thus reducing environmental pollution. Most importantly, the solution was cheap as fewer mosquito repellents and less energy were used.

In future studies, we will implement user feedback so that our model can learn from the user feedback on the classification results. This will improve the model further and ensure that it continuously learns in its environment, thus achieving the goals of the living lab. Additionally, we will roll out our proposed solution in schools and hospitals in Eldoret municipality, Kenya, for more feasibility studies. Last but not least, we will take advantage of the availability of smartphones to carry out citizen-centric crowdsourcing to collect and release mosquito wingbeat sounds in Kisumu county, Kenya, which would be used by the community in developing ML model which will accelerate the deployment of intelligent mosquito repellents.

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