This 100% Accurate Device Detects Perpetual Motion Machines. Bhaskara II in Shambles!

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Abstract

We introduce a novel device, termed the Perpetual Motion Detection System (PMDS), which utilizes a complex machine learning framework to detect and validate perpetual motion machines. The PMDS system was measured to have an accuracy of 100% in a double blind trial, exceeding the leading accuracy rates of any detection device created in the past. The PMDS system, which is both small and easy to carry, can be mass-produced and housed within any institution seeking to validate potential discoveries of infinite energy sources.

1. Introduction

The discovery of electricity and its consequences have been a disaster for the human race. From the moment Benjamin Franklin flew his kite into the thunderstorm above his house, the race for unbounded energy sources has never stopped. The term Perpetual Motion Machine is used to denote any such machine that can continuously function and do work without the need for an external energy source, thereby producing a net positive amount of energy. If such a machine was invented, its energy producing capabilities could be exploited to solve poverty, world hunger, and climate change, ushering in an age of omni-newable energy. So far, all of the leading research laboratories in this field have turned up empty handed. Figure 1 shows the most famous of these failures — the wheel created by Bhaskara Labs in 1146, which uses a system of tubes containing mercury to generate torque upon motion — as well as other examples [3].

A survey of the labs working in the perpetuality field reveals the extensive verification process of prototypes as a major pain point and source of delay in the research process. If a framework could be developed that quickly and definitely proved whether or not a machine is capable of perpetuality, development time would be sped up immensely, and the race for a Perpetual Motion Machine could come to an end. We explore the details of this framework, and showcase a device, the Perpetual Motion Detection System (PMDS), that implements it with 100% accuracy.

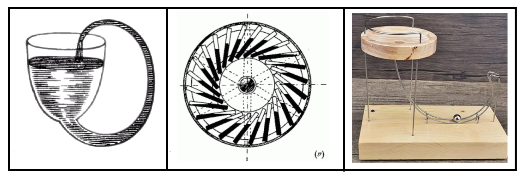

Figure 1. Examples of failed Perpetual Motion Machines. From left to right: Robert Boyle's Self Filling Flask, Bhaskara's wheel, Parabolic ball [4] [2]

2. Method

In order to detect whether or not a machine is capable of perpetual motion, we conjured up a convolutional neural network, called NRGNet, that can be trained on images of machines ranging in size from a transistor to a locomotive. This image set was obtained from MNIST (M'Adobe NStock Image Standard and Technology) without their permission and consists of 10,505,128 images [1]. The details of a convolutional neural network are trivial in 2025, and so will be glossed over. The Adobe Stock Image set was randomly split into a training set, consisting of 8,404,102.4 images, and a testing set, consisting of 2,101,025.6 images. The convolutional neural network was tasked with outputting a binary result of Yes or No, corresponding to whether or not it thought a test image was a Perpetual Motion Machine or not. The thought process of NRGNet is detailed in Figure 2.

After the neural network was trained on the MNIST image set, it was loaded onto an ATmega328 micro-controller and assembled into the PMDS system. A custom circuit board was outfitted to connect all the electronics, including an LCD display, a button, and a small camera used to capture images that would be fed into the neural network during use. These were all housed in a black plastic box.

3. Result

NRGNet was trained with multiple checkpoint epochs to obtain the highest accuracy numbers while minimizing validation loss. After each training session, the neural network was

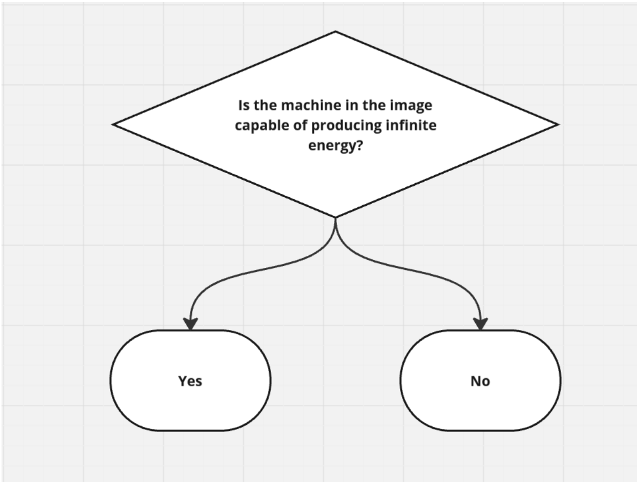

Figure 2. The decision tree utilized by NRGNet in the classification of Perpetual Motion Machines.

presented with images of machines from the validation set, and its performance was noted. Figure 3 details the result of each training epoch.

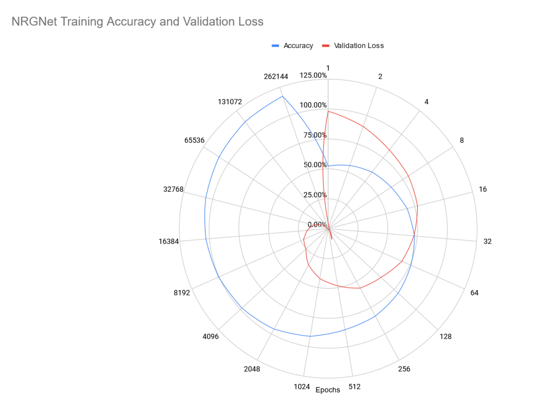

Figure 3. NRGNet training data presented in an obfuscated, yet ultimately legible manner.

During training, it was noticed that the NRGNet model was being a little too husky-sized with the data. A preferential factor, which would help account for the skewed fitting, was added to the NRGNet model, and the model was retrained. Figure 4 shows how this was implemented.

Testing of the PMDS system commenced with a total of 1000 sample machines. The tester wore two blindfolds, ensuring the absence of bias in the results. The PMDS system was held next to each of these machines, and after it gave its determination, the result was recorded and the next machine was brought in to be judged. Figure 5 shows an example test performed on the *felis catus*, which has been known to operate without batteries or charging.

It can be seen that the PMDS system displays a perpetuality determination of the subject in text form to the user.

```
bool NRGNet_AddPreferentialFactor(...)
{
    ...

    /* result is the value given by
       NRGNet before the preferential
       factor is added. */
    cout << The current classification is ";
    cout << result << endl;

    // Implementation of preferential factor
    if (result == true) {
        result = false;
    }

    return result;
}
```

Figure 4. Implementation of the NRGNet preferential factor. This implementation adds a trivial amount of overhead and results in an increase in correctness.

Figure 5. PMDS system showing the result of a test. The reading shows that the *felis catus* is not a perpetual motion machine.

Figure 6 shows the result of all the tests, with the PMDS system having recorded a 100% accuracy in gauging perpetual motion.

Here we have shown that the PMDS system boasts a staggering 100% accuracy rate, which is a unique trait among the class of detection devices. We fully expect to see every institution, academic or otherwise, that is in pursuit of a Per-

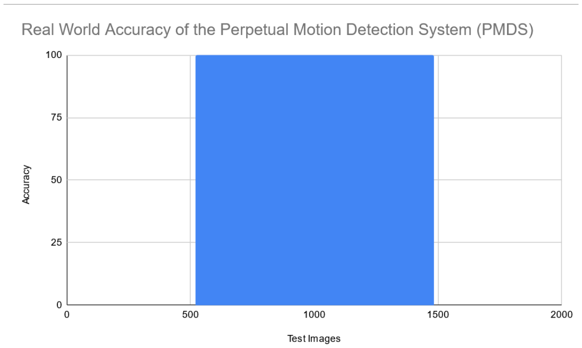

Figure 6. Double blind testing results of the PMDS system.

petual Motion Machine to leverage NRGNet and the PMDS system.

4. Future Work

Bhaskara II did not immediately respond to a request for comment.

References

[1] Adobe. 2025. M'Adobe NStock Image Standard and Technology (MNIST). In *Adobe Stock, February, 2025*.

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[4] Boyle Robert. 1651. Damn, I Wish I Had More Beer. In *Bartender Tools of the Trade: 8th Edition, April, 1651*.