# Deep Learning based Stable and Unstable Candle Flame Detection*

Amir Khan[1] and Mohammad Samar Ansari[2,1]

[1] Aligarh Muslim University, India
amiramu10@gmail.com
[2] Software Research Institute, Athlone Institute of Technology, Ireland
mdsamar@gmail.com

**Abstract.** This paper presents a deep learning based solution for identification of normal and abnormal candle flames, controlled and uncontrolled flames.Candle flames affected by external factors like wind, improper combustion of fuel etc. Proposed CNN based deep neural network can successfully classify the stable and unstable candle flame with an accuracy of 67% for generated test set and an accuracy of 83% for random images taken from open source on internet.

**Keywords:** stable flame · unstable flame · Deep Learning.

## 1 Introduction

Candle is one of the oldest illumination sources used by humans. Scientific study of candle flame is not new and dates backs to early civilization. Candles due to its availability and not being costly make them center of attraction for research. A domestic candle is an example of diffusion flame. Heat of the flame is utilized to melt the wax on the body of the candle and this molten wax is acquired by the wick through capillary rise and the fuel evaporates from the wick to maintain the flame. A candle flame is itself a closed surface and a stable flame has an axis-symmetric shape while the unstable flame may or may not be axis-symmetric. Candle flame differs from any other random fire as it reaches to steady state very soon. Candle though primarily the source of light but also an important element of decoration. According to Mintel (2013), total U.S. retail sales for candle products are 3.14 billion [1]. It has been estimated by National Fire Protection Association (NFPA), fire department in US has received 7900 calls annually to extinguish the fire at homes caused by candles for the period of 2013-2017 while the minor fires are unreported. An estimated average death toll due to fires is 80 while the number of injured persons are 720 along with the damages to property of worth $268 million. NFPA also pointed that home candles were the reason for the fire when some burnable substances were kept very close to candles [2]. NFPA has suggested many safety measures for candles but all of them are manual and involves human intervention, and one of them is

* Supported by University Women's Polytechnic, Aligarh Muslim University

to keep candles 1ft away from everything flammable/likely to catch fire, which requires an empty surrounding of 2ft diameter circle along with an added cost of rigid base or candle holder. As we all know carelessness of humans are inevitable. So, detecting an unstable flame can be the first step of precautionary measures. In addition, this information provides the efficiency of fuel consumption. A stable flame represents efficient fuel consumption, and provides pleasant aesthetic sense when used for decoration. Who would deny the importance of candle light dinner with your love? Ambience around the candle can be controlled in order to keep the flame stable and steady making the perfect shape. This study presents the classification of stable and unstable candle flame using the deep learning. This study is the first of its' kind in this direction using deep learning. Primarily, this classification is useful at houses, religious places like churches etc., as a first precautionary measure. NFPA recorded that there were on average 22 fire accidents daily and Christmas and Christmas were the most accident reporting days [2].

## 2 Related Work

Faraday [10] in his lectures explained the science behind the working of candles. Despite being ubiquitously present, systematically structured investigation of candle has not started very early but couldn't be left for long and ultimately attracted the researchers. Kosdon et al. [10] experimented the first known nearly organised experiment for studying the candle through observing the burning candle on a erected cylindrical surface. However, this study happened to be simpler as they approximated cylinder as a flat surface while the flame near the wick was three dimensional. Alsairafi et al. [6] modeled the fuel rise to wick i.e., capillary phenomena and dynamics of flame. Flame of Candle is an instance of diffusion flame and several researchers explored different features of diffusion flames. Ballester et al. [7] reviewed the existing techniques for diagnosis and control of practical flames. These techniques include various kinds of flames of fuels like bio-fuels, fossil fuels, gasoline, and various ratio of fuels and oxygen etc., and various techniques like flame spectroscopy, flame imaging, pressure fluctuation etc. have been used to study flames. Laminar smoke point of the candle flames has been explored by Allan et al. [5] by varying the diameters of the wick and the lenghts of candles for different type of waxes. Sundeland et al. [17] analyzed and measured the shape of the candle flames for different size candles and Roper laminar burner model for flame height has been used. Riley [14] used the flame sheet model proposed by Burke-Schumann to model the reaction zone of the candle flame while ignoring all other combustion processes which limits the scope of this study. The combustion of candles exhibits various dynamic characteristics and the flickering of group of candles have attracted many researchers. Hamins et al. [11] studied the burning behavior of candles and characterized the candle flame and developed the model for candle burning behavior. Buckmaster [8] proposed the theoretical explanation for the flickering, or oscillation of large diffusion flame and suggested an infinite candle paradigm to understand this phenomenon. Moreover, it is well known that diffusion flames flicker over frequency range of 10-20Hz. Chen et al. [9] studied the characteristics related to phase and frequency of oscillation for candle flames. They bonded several candles and studied the effect on flame frequency by considering the arrangement of candles, number and asymmetry of oscillators. They observed that the frequency slowly reduces with the count of candles when considering isolated oscillators and when two oscillators are coupled, switching between anti-phase and in-phase synchronization takes place. Wang et al. [18] studied the features of burning candle flame at pressures lower than atmosphere and also performed the scaling analysis to elucidate the dependence on pressure.

Field of machine learning research has found new and powerful sub-area famously known as Deep Learning (DL) or hierarchical learning. Deep learning is one of the most promising field being utilized to classify several task. From past multiple years DL is affecting myriads of applications in various fields of study like medical science, astronomy, market analysis etc. DL can perform classification better than any other existing techniques. One of the most utilized and chosen fundamental network is Convolutional Neural Network (CNN) of DL. Unlike the feed forward neural network, DL uses deep networks and one of the most used deep network is Convolutional Neural Network (CNN). Many researchers have exploited the enormous power of CNNs for classification task which were not possible, so accurately, by any other existing methods. DL has also been used to study the flame/fire extensively[3-5] [13] [16]. Muhammad et al. [13] have designed CNN for the early detection of fire during surveillance for effective disaster management. They have achieved an accuracy better than any of the presently available methods and two diverse datasets. Adedotune et al. [4] proposed an end-to-end deep selective autoencoder approach for the predicting instabilities in combustion process using the hi-speed flame video for an industrial combustor. Their proposed deep network can accurately identify the slight instability parameters as the combustion process changes state from stable to unstable. Li et al. [12] developed DL-based prediction model predicting the NOX radical emission from a biomass fires combustion process; developed model has been compared with the existing other machine learning based model and it has been demonstrated that DL-based model has surpassed all the existing models. Abdurakipov et al. [3] utilized CNN to monitor the flame regimes and achieved an accuracy of 98% for regime classification. Sarkar et al. [16] proposed a dynamic data dependent method where a huge number of sequential gray scale images are used to study the time-dependent variation of the combustion system for prior detection of instability at different working conditions by using deep neural network with Symbolic Time Series Analysis.

## 3 Dataset Details

In this study the data has been generated by a high resolution camera and for different types of candle. Different size and color candles of paraffin wax with different background have been used for dataset generation. Some of the images

**Fig. 1.** Sample Images

were captured on complete dark room while some of images captured in the light of an incandescent LED bulb of 12W. These different combinations have been used to generate a widely diverse data for training and testing. Captured images are of size 3024x4032 at a shutter speed of 2s. Stable flame images have been captured for controlled environment where there was almost no flow of air in any direction, even the observer kept a mask on his face while taking the snapshots. Flame has been made unstable by giving blows from the mouth of various amplitude and from various directions and angles. In both the cases different distances from the candle have been maintained while capturing the images. To facilitate further research on this topic, the authors have open-sourced the candle flames dataset[3]. Some randomly selected images from the collected dataset are shown in Fig. 1

[3] http://tiny.cc/ut0dlz

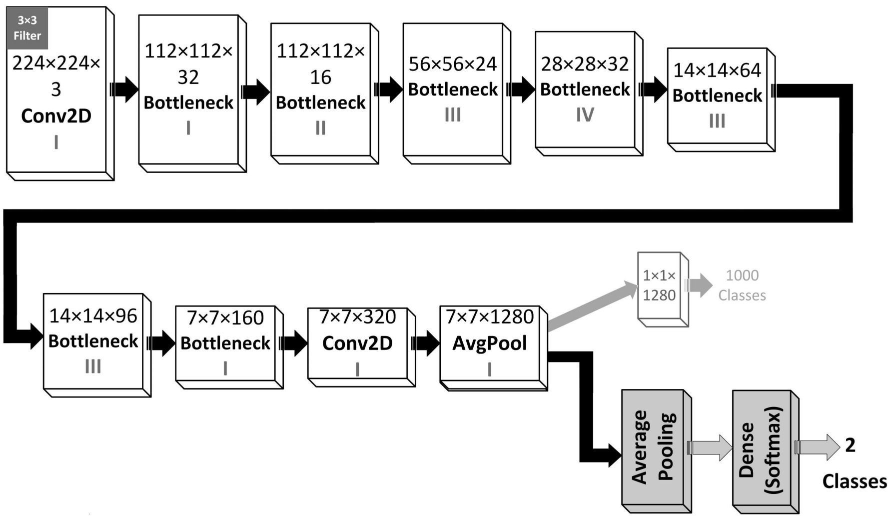


**Fig. 2.** Proposed architecture of the deep learning model used in this work. The greyed-out blocks show the layer(s) removed from the MobileNet$V2$ model,and the orange blocks show the added layer(s). Numbers in green denote the number of times the block is repeated. Detailed information about the internals of the various layers (except the ones added in this proposal, shown in orange), strides, and expansion factors can be obtained from [15].

## 4 Proposed Model

The age of high performance DL models for CV started with AlexNet in 2012. It was followed by better models like VGG, ResNet, Xception, and MobileNet.

**Table 1.** Details of the DL model.

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| Validation Split | 0.20 | Optimizer | Adam |
| Epochs | 200 | Activation (Output Layer) | Softmax |
| Batch Size | 20 | Loss parameter | Binary crossentropy |
| Learning rate | 0.001 | Trainable parameters | 2,230,277 |
| Decay | 0.00002 | Non-trainable parameters | 34,112 |

MobileNet was proposed as a DL model which is capable of AlexNet-like performance with a significantly reduced model size (∼21 MB size, 4.2 million parameters). More recently, MobileNet *V2* was proposed which is able to provide the same performance as MobileNet with even smaller model size (∼13 MB size, 3.4 million parameters) [15].

The original MobileNet *V2* was proposed for classifying 1000 image classes in light of the ImageNet challenge[4]. However, for the purpose of this work, we are interested in only 2 classes of images: normal candle flame, and abnormal candle flame. Therefore, suitable modifications in the original MobileNet *V2* need to be incorporated to make the model amenable for the task at hand. Toward that end, we froze the parameters of the initial layers in MobileNet *V2* and removed the last layer from the original model. Subsequently, we added an average pooling layer and a dense layer with 2 outputs (equal to the number of classes to be assigned) and Softmax activation at the output. The modified model is presented in Fig. 2, which results in a model size of 26.2 MB on disk with 2,264,389 parameters.

The proposed network was implemented in Keras which is a high-level neural network API capable of running on top of the deep learning framework TensorFlow$^{TM}$. The MobileNet *V2* model, with the modifications described above, was trained on the images from the train dataset (3,940 training samples with 20% of the training samples used for validation). The MobileNet *V2* weights, for all layers excluding the output layer, were initialized using the pre-trained weights for the ImageNet dataset, as available from Keras[5]. The model was compiled with the `Adam` optimizer using the `Binary Crossentropy` loss function, and `Accuracy` was used as the metric to monitor the training of the model. The model was trained for 200 epochs with a batch size of 20, and learning rate set to 0.001.

## 5 Results

The trained model was used to perform inference on a test dataset of 272 images comprising of images from the same 2 classes as the train dataset. The classification performance of the model was adjudged based on the accuracy of the classes assigned to the test images by the model. Overall, it was found that for the 272 test images, the model was able to correctly identify the correct class for approximately 67% of the test images. Fig. 3 presents some sample test results on images for the 2 categories. Fig. 3(a) depicts an example of a 'normal' candle flame image taken from the test dataset, and it can be seen that the model identifies it correctly with more than 90% certainty. Fig. 3(b) presents an image of a normal candle flame taken from the internet, and the trained model successfully identifies it as such with almost 100% certainty. Similarly, for the case of two 'abnormal' candle flame images (one from the test dataset shown in Fig. 3(c), one randomly taken off the internet shown in Fig. 3(d)), the model correctly identifies both of the images as belonging to the abnormal candle flame image class.

Furthermore, analysis was performed to ascertain the classification performance of the model for random candle images taken off the Internet. For such images (30 in number), the classification accuracy was found to be 83%.

[4] http://www.image-net.org/challenges/LSVRC/

[5] https://keras.io/applications/#mobilenetv2

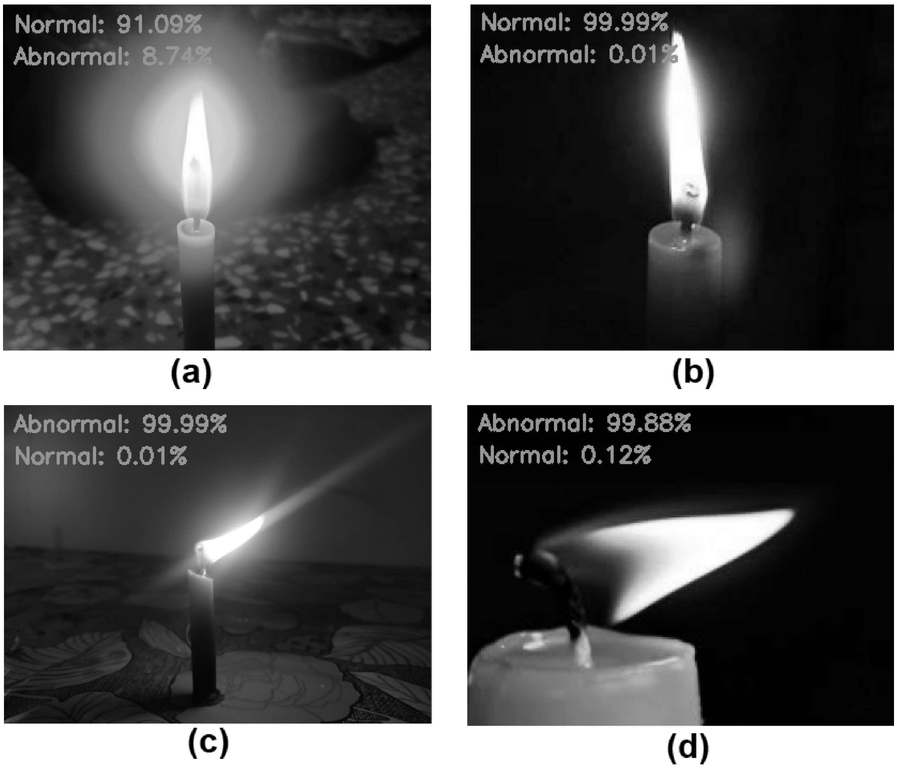


**Fig. 3.** Example results on some sample images from the test dataset as well as images taken from the Internet

The estimated probabilities of the 2 classes averaged over all the test samples of the respective classes are presented as the Confusion Matrix for a 2-class classifier, in Fig. 4. As can be seen from Fig. 4,

## 6 Limitations and Future Work

This work is limited in the sense that it proposes a classifier for the type of flame of candles. Scope of the work can be extended by providing the methods to control the environment to keep the flame stable, an efficient state for fuel consumption and gracious decoration sense. Furthermore, deep learning may also be utilized to study the flickering/oscillation of candle in particular and any other diffusion flame in general.

| | | Predition | |
|---|---|---|---|
| | | Normal | Abnormal |
| Ground | Normal | 81 | 11 |
| Truth | Abnormal | 3 | 89 |

(a)

| | | Predition | |
|---|---|---|---|
| | | Normal | Abnormal |
| Ground | Normal | 11 | 4 |
| Truth | Abnormal | 1 | 14 |

(b)

**Fig. 4.** Confusion matrix for the test results

## 7 Conclusion

Proposed work is first of its kind for the study of candle flame. Accuracy of the work can be further by increasing dataset size. Many researchers have applied deep learning in the diagnostic or prognostic of the combustion process to study the flame behavior for various combustor at different conditions.This work can be utilized for the precautionary measures to be taken in case of candle flame instability. Proposed work can be integrated with the CCTV cameras and can sound the alarm when it founds substantial instability which may cause fire or may burn the nearby materials.

## References

1. Candle-us-august 2013. https://store.mintel.com/candles-us-august-2013, accessed: 2019-03-12
2. Candles. https://www.nfpa.org/Public-Education/Fire-causes-and-risks/Top-fire-causes/Candles, accessed: 2019-03-12
3. Abdurakipov, S., Gobyzov, O., Tokarev, M., Dulin, V.: Combustion regime monitoring by flame imaging and machine learning. Optoelectronics, Instrumentation and Data Processing **54**(5), 513–519 (2018)
4. Akintayo, A., Lore, K.G., Sarkar, S., Sarkar, S.: Prognostics of combustion instabilities from hi-speed flame video using a deep convolutional selective autoencoder. International Journal of Prognostics and Health Management **7**(023), 1–14 (2016)
5. Allan, K.M., Kaminski, J.R., Bertrand, J.C., Head, J., Sunderland, P.B.: Laminar smoke points of wax candles. Combustion science and technology **181**(5), 800–811 (2009)
6. Alsairafi, A., Lee, S.T., T'IEN, J.S.: Modeling gravity effect on diffusion flames stabilized around a cylindrical wick saturated with liquid fuel. Combustion science and technology **176**(12), 2165–2191 (2004)
7. Ballester, J., García-Armingol, T.: Diagnostic techniques for the monitoring and control of practical flames. Progress in Energy and Combustion Science **36**(4), 375–411 (2010)
8. Buckmaster, J., Peters, N.: The infinite candle and its stability—a paradigm for flickering diffusion flames. In: Symposium (International) on Combustion. vol. 21, pp. 1829–1836. Elsevier (1988)
9. Chen, T., Guo, X., Jia, J., Xiao, J.: Frequency and phase characteristics of candle flame oscillation. Scientific reports **9**(1), 1–13 (2019)
10. Faraday, M.: The chemical history of a candle. Courier Corporation (2002)
11. Hamins, A., Bundy, M., Dillon, S.E.: Characterization of candle flames. Journal of Fire Protection Engineering **15**(4), 265–285 (2005)

12. Li, N., Lu, G., Li, X., Yan, Y.: Prediction of nox emissions from a biomass fired combustion process based on flame radical imaging and deep learning techniques. Combustion Science and Technology **188**(2), 233–246 (2016)
13. Muhammad, K., Ahmad, J., Baik, S.W.: Early fire detection using convolutional neural networks during surveillance for effective disaster management. Neurocomputing **288**, 30–42 (2018)
14. Riley, N.: A sheet model for the candle flame. Proceedings of the Royal Society of London. Series A: Mathematical and Physical Sciences **442**(1915), 361–372 (1993)
15. Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., Chen, L.C.: Mobilenetv2: Inverted residuals and linear bottlenecks. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 4510–4520 (2018)
16. Sarkar, S., Lore, K.G., Sarkar, S., Ramanan, V., Chakravarthy, S.R., Phoha, S., Ray, A.: Early detection of combustion instability from hi-speed flame images via deep learning and symbolic time series analysis. In: Annual Conf. of the Prognostics and Health Management (2015)
17. Sunderland, P., Quintiere, J., Tabaka, G., Lian, D., Chiu, C.W.: Analysis and measurement of candle flame shapes. Proceedings of the Combustion Institute **33**(2), 2489–2496 (2011)
18. Wang, Q., Hu, L., Palacios, A., Chung, S.H.: Burning characteristics of candle flames in sub-atmospheric pressures: An experimental study and scaling analysis. Proceedings of the Combustion Institute **37**(2), 2065 – 2072 (2019)