Skin cancer is a serious problem which kills 58,667 people each year with 331,722 new reported cases. However, it is a condition where the cost of visiting a doctor can delay its identification and gets worse the longer undiscovered. In particular the survival rate is around 99.9% if caught at stage 1, but by stage 2 is ~45-79%. Even worse at stage 4 survival is 7-19% depending on type. Therefore, an application which allows people to take images of lesions on their skin which could be cancerous and tell them if it should be checked by a doctor could save lives and money through early detection.

The dataset to train the model is from "https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DBW86T" and contains pictures of skin lesions with them labeled as cancerous or another type of lesion. There are 11,517 images labeled for training and testing. The model will likely be much more effective at determining skin cancer for lighter skin people. This is because the data is of lighter skinned people. However, 1 in 38 white, 1 in 167 Hispanic and 1 in 1,000 black people get skin cancer over their lifetime (treatcancer.com). Thus white people are about 26 times more likely to have skin cancer than black people making the majority of skin cancer, thus potential benefit, be captured by an application which works for lighter skinned people. Also, the larger proportion of skin cancer in lighter skinned people helps explain why the available data is heavily skewed towards them. It should also be noted that skin cancer tends to occur at different locations between different races. For example, black people tend to have it on their palms or the soles of their feet. Given less than 500 images exist for both in the HAM10000 dataset, training a machine learning model for black skin cancer (with very white hands and feet) does not seem possible. Even worse, around 30-40% of skin cancers in non-white populations occur in the plantar region (center of the bottom) of the foot. This is an issue as any application would be based on someone viewing an abnormality on their skin and taking an image of it to check. The bottom of the foot would be a lot less likely to be noticed than areas skin cancer tends to occur in white individuals. This includes the lower legs and other areas exposed to the sun (thus easily seen) which would be more likely to be spotted earlier and thus checked (treatcancer.com). Furthermore, any application to check for skin cancer would require individuals to proactively use it. Given lighter skinned people are at least 26 times more likely to have it over their lifetime, they will likely always be more proactive in checking for early skin cancer than black people who have a 1 in 1000 odds of ever experiencing it. In addition, techniques to help AI identify skin cancer seem to utilize the skin being lighter. For example, when removing hair from images of skin it being darker than the skin is helpful. However, darker skin would not work with these techniques (although I am not sure how relevant this is given skin cancer is usually on the bottom of feet or palms for black people. These areas do not have hair and tend to have lighter skin). In total, due to dealing with darker skin having small improvements to a potential models' impact, while making building it much harder any created model is very likely to only work for light skin.

Three-quarters of deaths come from malignant meloma. These are the cells responsible for producing pigment in the skin. Thus, any model should focus on catching these types of cancer early. In addition the study by Hu et al., had 55.4% of patients with melanoma diagnosed when local from 1997-2002 in Miami-Dade County, Florida. This means the cancer has spread to nearby tissue, but not beyond skin cells. Thus, the largest impact for any application seems to be early detection so the skin cancer can be detected in situ, before it has spread to surrounding tissue. Of note, the largest potential negative is failing to identify skin cancer, particularly in patients with a later stage. This is especially given the datasets will likely reflect when cancer is identified, thus skew towards being local (55.4%) or in situ(25.0%) (He et al., 2006). Thus, without proper weighting a model could prioritize getting early stage cancer correct over later stages. If incorrect, any model could convince someone with late stage skin cancer to not seek medical help and die when treatable.

Any model will be using the 11,157 images from Harvard and given descriptive information. This takes up 6.4GB so will need at least as much to store it. In addition Google Colab required 32.8GB of disk and 1.5 GB of RAM to run a test training model. This means around 39.2 GB of disk and 1.5 GB of memory space should be expected for use. The reason running the algorithm requires so much more disk space than the data is modules like tensorflow being used.

References :

https://treatcancer.com/blog/skin-cancer-by-skin-tone/

Hu S, Soza-Vento RM, Parker DF, Kirsner RS. Comparison of Stage at Diagnosis of Melanoma Among Hispanic, Black, and White Patients in Miami-Dade County, Florida. Arch Dermatol. 2006;142(6):704–708. doi:10.1001/archderm.142.6.704